Essays on Endogenous Technical Change in Climate Policy Analysis

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Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university. To the best of the author's knowledge and belief, it contains no material previously published or written by another person, except where due reference is made in the text.

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Abstract

This thesis consists of four papers studying endogenous technical change (TC) in climate policy analysis. The first paper (Chapter 2) provides a conceptual framework of the mechanism through which TC can be induced by climate mitigation policies. The second paper (Chapter 3) develops a computable general equilibrium (CGE) numerical model to quantitatively analyze the effect of endogenous TC on the timing and cost of carbon abatements. The third paper (Chapter 4) develops a multi-region CGE model to examine the mechanism of international technology diffusion and its effect on domestic carbon savings. The fourth paper (Chapter 5) analyzes the mechanism of international technology coordination resulting from reciprocal cross-nation knowledge spillovers and its implication for global climate governance.

The first paper, "Revisiting the mechanism of endogenous technical change for climate policy analysis", aims to reconcile the diverging specifications of endogenous TC in existing climate policy modeling literature. Drawing on the theory of R&D-induced TC, I provide a generalized framework to analyze the mechanism through which TC can be induced by climate mitigation policies. In the presence of emission control measures raising the costs of using fossil energy, the price signal induces profit-seeking private firms to undertake purposeful R&D investment (R&D inducement). As a result, the stock of economically useful knowledge is augmented by this purposeful R&D (knowledge creation). The accumulated knowledge capital is finally applied in a production process for technical upgrading, with an outcome of shifting out *production possibility frontier* and substituting knowledge for costly energy inputs (production TC).

The second paper, "Can technological innovation help China take on its climate responsibility? A computable general equilibrium analysis", examines the effectiveness of China's indigenous R&D and technological innovation to cut its carbon emissions. The mechanism of endogenous TC is incorporated into a CGE numerical model. R&D investment and knowledge creation is modeled as the endogenous behavior of profit-seeking private firms. The accumulated stocks of knowledge are applied in the production process to induce

TC. Results show that: 1) While China's indigenous R&D play a significant role to curb its carbon emissions, sole dependence on R&D may be far from sufficient to achieve China's pledged Copenhagen climate target, with complementary policies required to reinforce private R&D efforts; 2) Innovation policies including public R&D subsidy and intellectual property protection can help strengthen economy-wide R&D investment and further reduce emissions, but this complementary effect is still minor and insufficient to meet the stipulated emission cuts target; 3) Carbon taxation can create significant carbon-saving benefits and fulfill the pledged climate target, but this achievement is at the cost of economic losses. Induced technical upgrading, however, can partially mitigate the deadweight losses incurred by carbon tax distortion.

The third paper, "Can China harness globalization to reap domestic carbon savings? Modelling international technology diffusion in a multi-region framework", aims to examine the effect of globalization, particularly international technology diffusion, on reducing China's domestic carbon emissions. The single-country CGE model is extended into a multi-region framework, where both indigenous R&D and foreign technology diffusion (TD) are explicitly considered as two sources of endogenous TC for domestic carbon savings. The model systematically describes foreign TD through three diffusion channels of trade, foreign direct investment (FDI) and disembodied knowledge spillovers, with an elaborate treatment of local knowledge absorptive capacity. Results show that: (1) Foreign TD complements China's indigenous R&D to help reduce domestic carbon emissions, with the leading diffusion channel being disembodied spillovers in the short run and embodied diffusion (via import and FDI) in the long run; (2) Trade and FDI liberalization (economic globalization) facilitates economic integration and production growth, yet at the cost of higher emissions levels without carbon savings (*scale effect*); (3) Removal of foreign TD restrictions (knowledge globalization) can help China reap the benefits of domestic carbon savings (*technique effect*); (4) Domestic climate regulation can create the *composition effect* by inducing indigenous R&D and foreign TD to shift domestic economic composition, hence helping partially mitigate climate compliance cost.

The fourth paper, "International knowledge spillover and technology externality: Why multilateral R&D coordination matters for global climate governance", investigates the mechanism of international technology cooperation and its effect on lowering global climate mitigation cost, with an aim of exploring the possibility of complementing international emission-based agreements with technology cooperation in the post-2012 climate regime. For that purpose, this paper firstly presents an analytical framework that describes how the mechanism of international R&D coordination can work for climate change mitigation. This mechanism is then quantitatively examined in a multi-region global numerical model that explicitly considers multilateral reciprocal knowledge spillovers and resulting technology externality. Results show that: (1) By internalizing the reciprocal externality of knowledge spillover, multilateral R&D coordination, as compared to non-coordinated innovation, can induce more R&D efforts of individual countries and hence global provisions of knowledge (public goods) that favor innovation across countries; (2) Enhanced innovative efforts under international R&D coordination facilitate accumulation of knowledge assets, which stimulate higher potentials of economic growth and carbon savings in all participating countries; (3) Multilateral R&D coordination (international technology-oriented agreements) can synergize with conventional emission-based climate agreements to help lower climate compliance costs, hence raising the participation incentives of major carbon emitting countries and the environmental effectiveness of their collective efforts in global climate mitigation.

Contents

Chapter 1

Introduction

1.1 Research Motivation

The threat of climate change, potentially caused by the growing atmospheric buildup of greenhouse gases (GHG), has led to an increasing number of numerical models for climate policy analysis. Numerous modeling studies have shown the sensitivity of the projections of climate mitigation cost and benefit to assumptions about technology, with the treatment of technical change (TC) being a key determinant of the simulation results in terms of the likely timing and cost of carbon abatement (Carraro and Siniscaico, 1994; Grubb, 1997; Carraro, 1998; Grübler and Messner, 1998; Grübler et al., 1999; EMF, 2004; Gillingham et al., 2008).

Generally, TC can be understood as an alteration in the character of production activity to enable more outputs to be produced with the same quantities of inputs through the process of invention, innovation, and diffusion of technologies. However, the complex mechanisms underlying this process are not appropriately captured in climate policy modeling framework, creating difficulties to determine the effect of emission control policies that is inevitably intertwined with technologies used in energy systems and the broader economy (Nordhaus, 2002; Sue Wing, 2006; Gillingham et al., 2008).

To incorporate the mechanism of TC into climate policy models, endogenous treatments choose specifying a feedback mechanism by which climate mitigation policies can induce TC biased toward carbon saving. This feedback may occur through the channels such as changes in the relative prices of inputs, research and development (R&D), and learning through production experience accumulation (learning-by-doing). This contrasts with exogenous treatments on the rate and bias of TC, which are unresponsive to the impact of climate policy regulations (Löschel, 2002; Gillingham et al., 2008).

While existing climate policy models have contributed to representing TC via various endogenous channels, their specifications tend to diverge with little consensus on the process of innovation. The main reason for this divergence is perhaps a lack of deep understanding of the mechanism of endogenous TC for climate mitigation. Therefore, the goal of the first paper is to elucidate, in a conceptual framework, how emission control policies induce TC, and how these in turn influence the economic costs of emissions controls. By doing that, I aim to reconcile the disparate efforts of modeling TC in the existing literature, and provide methodological guidance to modelers who are looking to either incorporate endogenous TC or refine existing TC specification in climate policy modeling.

While providing intuitions to understand the process of endogenous TC in climate mitigation, the simple analytical framework presented in the first paper is not well suited to quantitatively examine the endogenous TC and its effect on the cost and benefit of carbon emissions abatement. Since carbon abatement policies not only generate direct adjustments within energy markets, but also induce indirect general equilibrium effects on other markets which in turn have subsequent feedback effects on energy markets and the overall economy, a realistic climate policy model should feature a general equilibrium framework explicitly considering the price-dependent interactions between energy system and the rest of the economy. The method that serves this purpose is called a Computable General Equilibrium (CGE) model. In the spirit of the Arrow - Debreu model that captures the interactions of microeconomic agents in a decentralized market, the CGE models have become a standard tool for analyzing the economy-wide impact of climate mitigation policies (Goulder and Schneider, 1999; Sue Wing, 2001, 2003; Otto et al., 2008; Löschel and Otto, 2009).

In this context, the second paper is motivated to incorporate the mechanism of endogenous TC into a numerical CGE model, so that the effect of endogenous TC on the cost and benefit of emission abatement policies can be quantitatively examined. In particular, the focus of my investigation is on the effectiveness of China's technological innovation to curb its carbon emissions. This is primarily because China has become the world's largest carbon emitter, and its emission levels will continue to rise rapidly in line with its industrialization and urbanization. If the goal of global climate stabilization is to be achieved, China's carbon emission levels should be stabilized, which necessitates massive reductions in uses of energy commodities through raising the costs of fossil energy inputs. This implies potentially high economic costs in adjustment to the shock of emission control policies, so the extent to which R&D investment and technology innovation can be induced is critical to the economic costs of complying with climate commitment.

While indigenous innovative efforts are critical to domestic technology development and carbon savings, foreign technology diffusion also plays an important role to complement indigenous R&D in accelerating low-carbon innovation. This is particularly relevant to China in the current context of globalization. China's integration into the world economy through trade, FDI, human capital mobility, and technology cooperation provides various channels of foreign knowledge diffusion to favor domestic innovation, which further creates significant opportunities for improving China's environmental performance.

More importantly, with the issue of international technology transfer placed high upon climate negotiation agenda (IPCC, 2000), there is a pressing need in our research community to investigate the scope, potential, and method of international technology diffusion for low-carbon innovation (Grubb et al., 2002; Philibert, 2004; Popp, 2006a). Modeling international technology diffusion thus becomes a fruitful avenue for future climate policy analysis (Popp, 2006a; Gillingham et al., 2008; Popp, 2009; Popp et al., 2010b).

Therefore, the third paper is motivated to advance the existing studies that only model indigenous innovation within a closed economy. It extends the single-country model into a multi-region global framework, where the mechanism of international technology diffusion is incorporated. Based on this extended framework, the potential of international technology diffusion to complement domestic innovation for climate mitigation can be quantitatively examined.

Building on the multi-region global model developed in the third paper, the final paper aims to articulate the positive technology externality resulting from cross-country reciprocal technology diffusion, and explore the mechanism of international technology coordination for global climate governance. Such an attempt is particularly important, because current climate regimes that solely rely on international emission-based agreements (e.g., the Kyoto Protocol) become increasingly flawed, it is necessary to consider whether international technology cooperation can complement the conventional emission-based agreement for lowering climate compliance costs in the post-2012 climate architecture (Aldy et al., 2003; Barrett, 2003; Barrett and Stavins, 2003; Newell, 2008).

1.2 Thesis Structure

With the aim of studying endogenous TC in climate policy analysis, the thesis is organized as follows:

Chapter 2 provides a conceptual framework of analyzing the mechanism through which TC can be induced by climate mitigation policies.

Chapter 3 incorporates the mechanism of endogenous TC into a CGE numerical model, based on which the effect of China's indigenous R&D and technological innovation on the cost and benefit of carbon emissions abatement is quantitatively examined.

Chapter 4 extends the single-country model into a multi-region global framework which fully describes international technology diffusion through various channels in the context of globalization. This extended model is then employed to analyze the effect of foreign knowledge inflows on China's technology innovation and domestic carbon savings.

Chapter 5 investigates how international technology cooperation works to internalize the reciprocal technology externality in global climate governance, both analytically and numerically, with an emphasis on whether international R&D coordination can be harnessed to synergize with traditional emission-based agreement for lowering climate compliance costs.

Chapter 6 concludes by summarizing the main findings concerning the endogenous TC in climate policy analysis, and discussing future work to be undertaken.

Chapter 2

Revisiting the Mechanism of Endogenous Technical Change for Climate Policy Analysis

Abstract: Numerous climate policy studies that model endogenous technical change (TC) have emerged in the literature, but their endogenous specifications tend to diverge with little consensus on the underlying process of innovation and TC. To reconcile disparate modeling methods, this paper revisits the mechanism of endogenous TC in climate policy analysis by developing a conceptual framework that captures three endogenous processes: R&D inducement, knowledge creation, and production TC. I also provide methodological implications on how to incorporate this mechanism into a multi-sector computable general equilibrium (CGE) model, particularly the treatment of cross-sector knowledge spillovers and R&D crowding-out. Building on this generalized conceptual framework, climate policy modeling that seeks to incorporate endogenous TC can hopefully be supported in future studies.

Keywords: Endogenous Technical Change; R&D; Climate Policy Model

2.1 Introduction

One of the important yet complex questions in modelling climate policy is the appropriate treatment of technical change (TC). The approach used in modeling TC is a key determinant of the results of climate policy analysis, particularly the likely timing of carbon abatement and associated cost and benefit. Generally, TC can be understood as an alteration in the character of productive activity to enable more outputs to be produced with the same quantities of inputs through the process of invention, innovation and diffusion of new technologies (Nordhaus, 2002; Sue Wing, 2006; Gillingham et al., 2008). Unfortunately, the underlying complex mechanisms are not readily captured in the existing modeling studies, creating difficulties to comprehend the potential role of TC in climate change mitigations.

Until recently, the widespread methods of modeling TC in climate policy analysis were to consider it as an exogenous variable. A simple approach is to assume a Hicks-neutral productivity growth that governs the overall rate of TC, but this method fails to capture TC that is potentially directed towards energy savings. An easy modification that reflects an energy-saving bias of TC is to include autonomous energy efficiency improvement (AEEI) parameters that govern changes in energy use efficiency as a function of time horizon (e.g., Nordhaus, 1994; Böhringer, 1998; McKibbin and Wilcoxen, 1999; MacCracken et al., 1999). This approach, however, is also challenged for the AEEI parameters not being "deep" structural with its unresponsiveness to climate policy intervention.

Development of alternative treatment of exogenous TC has been driven by the demand for normative analysis of climate technology strategies that should appropriately consider TC. This necessarily requires the basic positive questions to be answered unequivocally: what induces innovation and technological progress, and which endogenous processes are involved in the process of TC (Löschel, 2002; Sue Wing, 2003; Clarke et al., 2008; Gillingham et al., 2008). Only by comprehending the underlying mechanism of TC, numerical modeling studies can ensure a mature treatment of endogenous TC in statements about the likely timing and cost of carbon abatement.

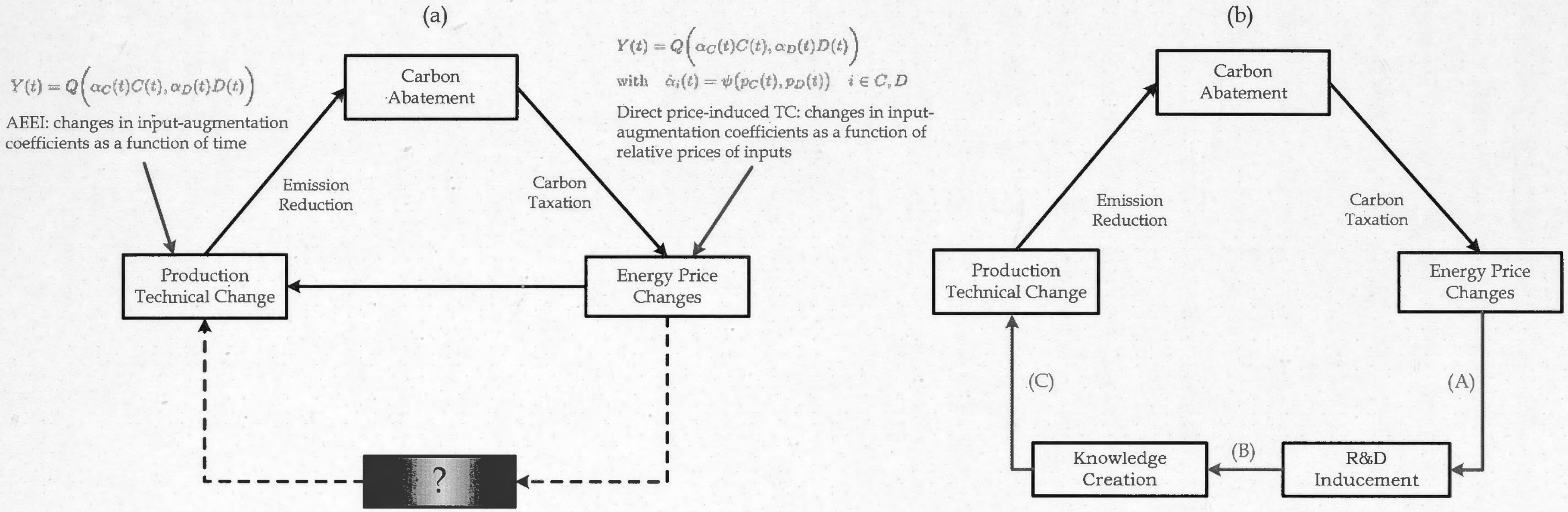
Generally, there is a wide literature acknowledging that TC is a complex process that does not just depend on the passage of time. This view has motivated considerable works on modeling the feedback mechanism through which the rate and bias of TC are affected by a variety of factors - current and expected energy price, R&D, or learning through production experience accumulation (Arrow, 1962; Newell et al., 1999; Azar and Dowlatabadi, 1999; Grubb et al., 2002; Jaffe et al., 2003; Bahn and Kypreos, 2003; Manne and Barreto, 2004).

A relatively straightforward method is direct price-induced TC, which suggests that changes in the relative prices of production inputs would induce TC that lowers the use of factors that become relatively expensive - the induced innovation hypothesis (Hicks, 1932). In explicit, this approach captures this phenomenon by specifying a production function in which factor inputs are augmented by technical coefficients.[1] As Fig. 2.1(a) illustrates, a unique final good Y is assumed to be made by combining carbon-intensive "dirty" input D with carbon-free "clean" input C. The AEEI method treats TC by specifying (exogenously) input-augmentation coefficients as an autonomous function of time. In contrast, the method of price-induced TC specifies (semi-endogenously) input-augmentation coefficients as *ad hoc* functions of changes in the relative prices of inputs, reflecting the TC directed at lowering the uses of "dirty" inputs that become relatively expensive under emissions control policies (Jacoby et al., 2003; Jackman et al., 2004; McFarland et al., 2004).

The direct price-induced TC does have merit as a partial explanation: higher prices of fossil energy would induce a shift to energy-efficient technological alternatives that use less fossil fuel. However, like the AEEI, it is still challenged for not being a "deep" structural formulation. From a perspective of microeconomic foundation, TC *per se* is a reconfiguration of production factors as an outcome of applying new knowledge in production (Goulder and Schneider, 1999; Sue Wing, 2001). The energy-saving effect of raising fossil fuel price is not directly on technology, but on stimulating the innovative incentives of private firms to create new knowledge. Accordingly, the price-induced TC still fails to unveil the black box of technology, obscuring some important details of the underlying mechanism by which emission control policies induce TC. Meanwhile, the lack of empirical foundation for the *ad hoc* functional forms of price-induced input augmentation also stifles its wide application, and it has been passed over to the next-generation method: R&D-induced TC.

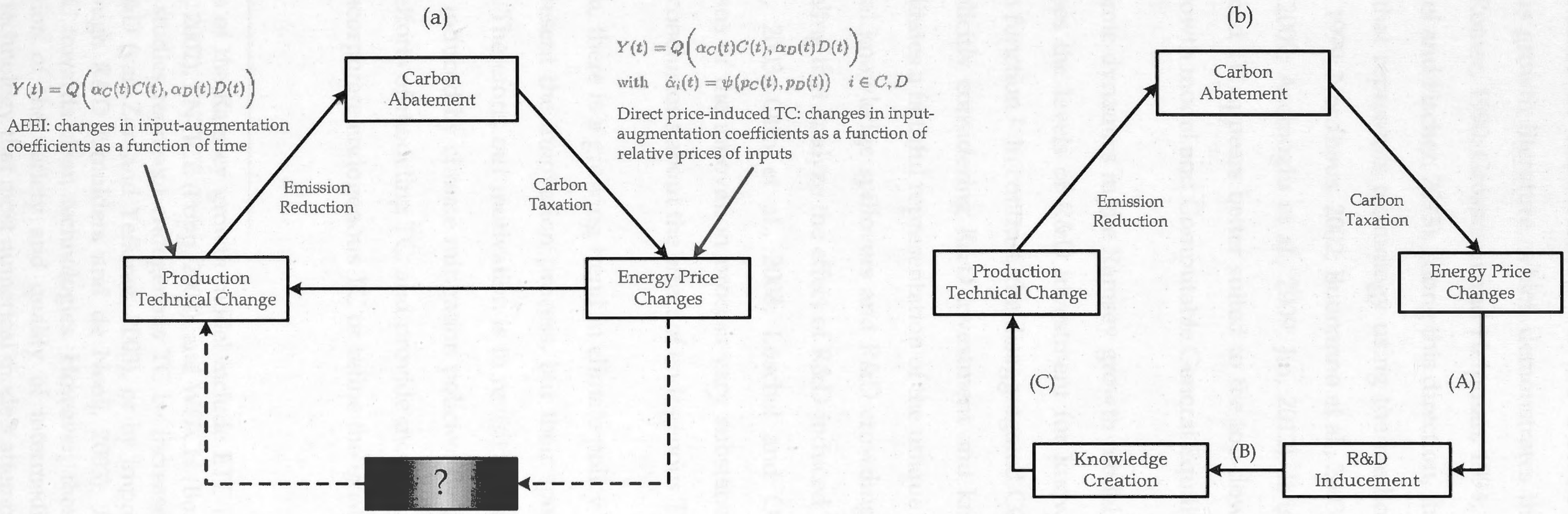
[1] The consequence of is that the physical quantities of production inputs remain unchanged, but the efficiency of input use cause its contribution to alter according to the value of augmentation factors, giving rise to different levels of output.

Figure 2.1: Exogenous and endogenous methods of representing technical change (TC) in climate policy models:



Note: (a) Exogenous methods of AEEI and direct price-induced TC. A unique final good Y is produced by combining "clean" input C and "dirty" input D. TC is represented by changes in input-augmentation coefficients a_C, a_D as a function of either time t or input prices P_C, P_D. Both exogenous (or semi-endogenous) methods treat the mechanism of TC as a black box; (b) A process-based representation of the endogenous TC mechanism based on the endogenous economic growth theory.

Figure 2.1: Exogenous and endogenous methods of representing technical change (TC) in climate policy models:



Note: (a) Exogenous methods of AEEI and direct price-induced TC. A unique final good Y is produced by combining "clean" input C and "dirty" input D. TC is represented by changes in input-augmentation coefficients a_C, a_D as a function of either time t or input prices P_C, P_D. Both exogenous (or semi-endogenous) methods treat the mechanism of TC as a black box; (b) A process-based representation of the endogenous TC mechanism based on the endogenous economic growth theory.

The method of R&D-induced TC has theoretical origins in the second-generation endogenous growth literature, which demonstrates the link between R&D and technology progress (Romer, 1990; Grossman and Helpman, 1994; Aghion and Howitt, 1998; Acemoglu, 2002; Heutel and Fischer, 2013). Along this direction, this is a growing trend in climate policy modeling that represents technology using the method of R&D-induced TC (Goulder and Schneider, 1999; Nordhaus, 2002; Buonanno et al., 2003; Popp, 2004; Sue Wing, 2006; Löschel and Otto, 2009; Acemoglu et al., 2009; Jin, 2012). It is also recognized that the method of R&D-induced TC appears better suited to the top-down modeling framework that includes Ramsey growth model and Computable General Equilibrium (CGE) model.

Economic dynamics in the Ramsey growth model are characterized by a social planner who chooses the levels of R&D investment for knowledge accumulation in an aggregate production function.[2] In contrast, the disaggregated CGE structure endogenously represents TC by explicitly considering R&D investment and knowledge creation at the sector level, which facilitates a faithful representation of the unique characteristic of knowledge including intersectoral knowledge spillovers and R&D crowding-out. Although there exist numerous CGE modeling that analyze the effect of R&D-induced TC (e.g., Goulder and Schenider, 1999; Sue Wing, 2003; Otto et al., 2008; Löschel and Otto, 2009), model assumptions and specifications of the innovation process vary substantially among these studies, leading to diverging conclusions about the effect of endogenous TC on climate mitigation.

In sum, there is a growing trend in climate policy modeling that uses the R&D-induced TC to represent the innovation process, but their specifications tend to diverge with little consensus. Therefore, our motivation is to revisit the underlying mechanism through which TC can be induced by climate mitigation policies. By doing that, I aim to help reconcile the disparate efforts of modeling TC, and provide methodological guidance to modelers looking to either incorporate endogenous TC or refine the existing TC specification in climate policy modeling.

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[2] Examples of the Ramsey growth model include ETC-DICE (Buonanno et al., 2003), R&DICE (Nordhaus, 2002), ENTICE (Popp, 2004), and WITCH (Bosetti et al., 2007). As an extension, some theoretical studies represent endogenous TC by increases in the variety of intermediate goods through R&D (van Zon and Yetkiner, 2003), or by improvement in the quality of intermediate goods through R&D (Smulders and de Nooij, 2003). Acemoglu (2009) presents a theory of directed TC towards clean technologies. However, these theoretical models with an abstract representation of the variety and quality of intermediate goods are not well-suited to the real-world technology that most numerical models attempt to specify.

The paper is organized as follows: Section 2.2 presents a conceptual framework of endogenous TC in the context of climate mitigation, with an emphasis on three consecutive processes: R&D inducement, knowledge creation, and production TC. Section 2.3 provides methodological implications on how to incorporate the endogenous TC mechanism into a multi-sector CGE modeling framework. Section 2.4 concludes.

2.2 Conceptual Framework of Endogenous TC

In the spirit of Goulder and Schneider (1999) and Sue Wing (2001), the conceptual basis of modeling endogenous TC is to treat technology as an accumulated stock of economically useful knowledge, which is augmented by R&D investment in the process of innovation. The created knowledge capital is then applied in the production process together with tangible physical inputs (e.g., labor, physical capital), which induces a reconfiguration of production factors for production TC.

To elaborate this intuition, I formulate a process-based representation of the mechanism by which climate policies induce TC. As illustrated in Fig. 2.1 (b), capping or taxing carbon emissions raise the cost of fossil energy inputs, and the signal of higher energy price not only generates substitution among production inputs in a traditional manner, but also induces private firms to undertake innovative activities in the form of R&D investment (Process A). As an outcome, knowledge stock is augmented by the purposeful R&D investment (Process B). Finally, the accumulated knowledge capital is applied in a production process for technical upgrading, with an outcome of shifting out *production possibility frontier* and substituting knowledge for costly energy inputs (Process C).

The remainder of this section provides a detailed exposition on the three consecutive endogenous processes, including: (a) Why increases in fossil energy price induce private firms' incentives of R&D investment; (b) How knowledge is created as an outcome of R&D investment; and (c) What's the effect of applying knowledge on production TC.

2.2.1 Inducement of R&D

Before turning to the formal analysis of R&D incentives, it is necessary to distinguish the driving forces of innovation between scientific breakthroughs and economic incentives. From a "science-driven" perspective, macro-level innovations are mainly driven by the exogenous breakthrough of scientific and engineering knowledge in a particular field, with an emphasis on the autonomous progress taking place as scientists build on each other's work, rather than the opportunities of profit. In contrast, most economists believe that economic profitability plays a more important role in stimulating technological innovation. At the micro level, in hundreds of cases the stimulus of innovation was the recognition of a costly problem to be solved or a potentially profitable opportunity to be seized. Since our purpose is to endogenize the innovation process in the economic context, I hence model TC as a consequence of purposeful economic activities by profit-seeking firms.

Drawing on the intuitions from Acemoglu (2009), I introduce an analytical framework that investigates the inventive response of private firms to fossil energy price increase in the Process A. Consider that in a partial equilibrium environment, there are a large number of competitive firms in an industrial sector, with access to an existing technology that enables firms to produce output at marginal cost, MC>0. The demand side of this industry is modeled with a downward-sloping demand curve, $D=D(P)$, where P is the product price and D is the market sale at that price. Assume that the demand function is strictly decreasing, continuously differentiable and satisfies the following conditions:

$$D(MC)>0, \qquad \xi_D=-\frac{dD(P)/D(P)}{dP/P}=-\frac{P\cdot D'(P)}{D(P)}>1 \tag{2.1}$$

where the first term in Eq. (2.1) describes that there is a positive demand when prices equal to the marginal cost, and the second requires that the price elasticity of demand ξ_D is greater than unity which ensures the existence of a well-defined monopoly pricing rule.

Since there is a large number of competitive firms with the same level of technology, one of these firms in this industry, say firm i, should charge a price that equals the marginal cost, $P_i = MC$, in the equilibrium without innovation. Thus regardless of its product sale, the profit of the firm i in this equilibrium will be zero, $\Pi_i = D_i \cdot (P_i - MC) = 0$.

Now turn to analyze the incentives of this firm to undertake innovation for profit gains. Suppose that this firm has access to R&D activities for product innovation. It innovates by reducing the marginal cost of production from MC to $\lambda \cdot MC$ by a factor $\lambda = \lambda(R_i)$, once it spends a R&D cost $R_i > 0$. The marginal cost reduction factor is a function of R&D

investment, which satisfies the following conditions:

$$\lambda = \lambda(R_i) \in (0 \;\; 1), \qquad \xi_R(R_i) = -\frac{d\lambda(R_i)/\lambda(R_i)}{dR_i/R_i} = -\frac{R_i \cdot \lambda'(R_i)}{\lambda(R_i)} \in (0 \;\; \infty) \tag{2.2}$$

where the first term in Eq. (2.2) expresses decline in the marginal cost of production λ as an outcome of R&D expenditure R_i. The second defines the R&D elasticity of innovation success $\xi_R(R_i)$ that indicates the uncertainty associated with research activities. That is, a higher value of $\xi_R(R_i)$ implies a higher probability of innovation success, where the marginal cost of production is more likely to decline once private firms invest in R&D.[3]

Consider that intellectual property protection (patenting systems) exists to ensure the excludability of innovation, thus the innovator will enjoy *ex post* monopoly power after innovation success. In other words, if individual firm i undertakes a successful innovation and has better technology than other firms, the *ex post* monopoly power will enable this firm to earn monopoly profits as, $\Pi_i = D(P_i)\cdot(P_i - \lambda\cdot MC) - R_i$. Maximization of this profit yields the standard monopolistic pricing rule as follows:[4]

$$P_i = \frac{\lambda \cdot MC}{1 - \xi_D^{-1}} \tag{2.3}$$

where the monopoly price charged by the innovating firm is a constant markup over the reduced marginal cost $\lambda \cdot MC$. Assume that the innovation is drastic with a sufficiently low value of λ, so that the firm can set an unconstrained monopoly price $P_i < MC$ and capture the entire market. Given the condition of $\xi_D > 1$, the monopoly price charged by the innovating firm is higher than the marginal cost of production $P_i > \lambda \cdot MC$, creating positive sales revenue $D(P_i)\cdot(P_i - \lambda \cdot MC) > 0$. In that case, the sales revenue is likely to exceed R&D expenditure R_i, creating a positive profit gain $\Pi_i > 0$. As compared with zero profit in the equilibrium without innovation, the firm has an incentive of undertaking R&D.

[3] A normal distribution $\xi_R \sim N(\mu, \sigma^2)$ can be used to represent the uncertain innovation. The lower bound $\xi_R \to 0$ means R&D failure: no response of innovation success (marginal cost reduction) to R&D investment. The upper bound $\xi_R \to \infty$ means technological breakthrough: a drastic cost decline as an outcome of R&D expenditure. The central value $\xi_R = \mu$ represents the average efficiency of R&D in a deterministic case.

[4] First order condition of profit maximization yields $D'(P_i)\cdot(P_i - \lambda\cdot MC) + D(P_i) = 0$, from which the monopolistic pricing rule can be derived.

If there are positive R&D expenditures, the *free entry condition* (FEC) of research can be used to pin down the sector-wide R&D investment in equilibrium as follows:

$$R = D(P)\cdot(P-\lambda\cdot MC) = \Phi(D,P,\lambda,MC) \tag{2.4}$$

where the equilibrium level of R&D investment R is expressed as a reduced-form implicit function, with four arguments: market price P, market demand D, marginal cost reduction factor λ, and the marginal cost of production MC. Given that climate mitigation policies raise the price of fossil energy P_E, its effect to induce R&D investment can be characterized through the following expression:[5]

$$\frac{\partial R}{\partial P_E} = \left[\underbrace{\frac{\partial \Phi}{\partial MC}\cdot\frac{\partial MC}{\partial P_E}}_{(1)} + \underbrace{\frac{\partial \Phi}{\partial P}\cdot\frac{\partial P}{\partial P_E}}_{(2)} + \underbrace{\frac{\partial \Phi}{\partial D}\cdot\frac{\partial D}{\partial P}\cdot\frac{\partial P}{\partial P_E}}_{(3)}\right]\cdot\underbrace{\left[1+\frac{\partial \Phi}{\partial \lambda}\cdot\frac{\lambda}{R}\cdot\xi_R\right]^{-1}}_{(4)} \tag{2.5}$$

where in a partial equilibrium environment, the inducement effect of climate mitigation policies on R&D investment depends on the interactions of four factors:

1) *Input cost effect* (first term): Carbon taxation, by raising fossil-energy price, imposes a higher marginal cost of production, $\partial MC/\partial P_E > 0$. As the production cost increases, the profit-seeking firm faces a reduction in profit and hence shrinking resources available for R&D investment, $\partial\Phi/\partial MC < 0$ - the negative effect on R&D inducement.
2) *Output price effect* (second term): Higher marginal cost of production incurred by carbon taxation would translate into a higher monopoly pricing charged by the innovator, $\partial P/\partial P_E > 0$. As the price of its produced product rises, the innovating firm can gain more sales revenues and profits, creating more resource available for R&D investment, $\partial\Phi/\partial P > 0$ - the positive effect on R&D inducement.
3) *Market demand effect* (third term): Due to a downward-sloping demand structure, the higher charged price is accompanied by a falling market demand, $\partial D/\partial P < 0$. As the market size shrinks, product sales revenues and profits decline, precipitating a reduction in resources for R&D investment, $\partial\Phi/\partial D > 0$ - the negative effect on R&D inducement.[6]

[5] For the derivation from Eq. (2.4) to Eq. (2.5), see Appendix 2.A.

[6] Market demand effect, combined with the following innovation risk effect, provides an explanation to the traditional "technology-push/market-pull" interaction in the process of innovation (e.g., Mowery and Rosenberg, 1979; Jaffe et al., 2005; Taylor, 2008)

4) *Innovation uncertainty effect* (fourth term): A higher value of ξ_R implies a higher probability of innovation success, where the marginal cost of production is more likely to decline as an outcome of R&D. Once the production cost falls, the firm can gain more profits and hence the resources available for R&D, $\partial\Phi/\partial\lambda < 0$ - the positive effect on R&D inducement.[7]

2.2.2 Knowledge Generation

Upon understanding the inducement of R&D in the process (A), the next issue is to examine how the induced R&D investment augments the stock of knowledge capital - the process (B).

In general, the knowledge creation process can be characterized as the R&D investment augments the knowledge stock according to a perpetual inventory assumption. However, to put this intuition into a specific modeling framework, I need to make an assumption about the characteristics of knowledge spillovers, which involves a methodological taxonomy as:

$$H_i(t+1) = R_i(t) + (1-\delta)\cdot H_i(t) \tag{2.6}$$

$$H_i(t+1) = R(t) + (1-\delta)\cdot H_i(t) = \sum_i R_i(t) + (1-\delta)\cdot H_i(t) \tag{2.7}$$

where Eq. (2.6) describes the process of knowledge creation without cross-sector R&D spillovers, where the knowledge stock specific to an individual sector H_i is augmented by sector-specific purposeful R&D investment R_i. This specification assumes that knowledge created by R&D is an asset with heterogeneous characters across sectors, so the knowledge created in different sectors is completely different entities that are not mobile across sectors (no R&D spillover). This is implied by the excludability of innovation: The innovating firm can completely appropriate the benefit from creating a better technology.

In contrast, Eq. (2.7) represents the process of knowledge creation with cross-sector R&D spillovers, where the knowledge stock specific to an individual sector H_i is augmented by economy-wide R&D investment $R = \sum_i R_i$. This treatment assumes that knowledge created

[7] Climate economists recently began to investigate the role of uncertainty in modeling TC. For a survey, see Baker and Shittu (2008). For the studies on the effect of uncertainty on technological innovation and climate policy design, see Basetti and Tavoni (2009), Blanford (2009), Held et al. (2009). For using an expert elicitation method to quantify the relationship between R&D cost and innovation success, see Baker et al. (2009).

by R&D is a publicly accessible good with homogenous characteristics across sectors, so the knowledge created in one sector are general-purpose that can freely spill over to other sectors. This is implied by the non-rivalry of knowledge: the general-purpose knowledge is characterized by its potential for pervasive use in a wide range of sectors, with spillovers and wide applicability as its general attribute (Bresnahan and Trajtenberg, 1995; Helpman, 1998; Clarke et al., 2006). [8]

Basically, these two alternative specifications represent different views about the characteristics of knowledge: the excludability of innovation *vis-a-vis* the non-rivalry of ideas. On the one hand, specification of Eq. (2.6) tends to reflect the heterogeneity of sector-specific knowledge - the "economics" property of knowledge. That is, technology innovation in an economic setting is largely an economic behavior which, like other economic activities, takes place for the purpose of pursuing profitability. To design new "blueprints" and appropriate resulting economic benefits, profit-seeking firms will spontaneously create tacit and specific knowledge that is largely distinct and excludable to its competitors. On the other hand, the specification of Eq. (2.7) suggests the wide applicability of general-purpose knowledge – the "science" property of knowledge. That is, given that the non-rivalry and spillovers are the general attributes of basic scientific knowledge, the general-purpose knowledge embodied in the invented "blueprints" can be re-used directly in different contexts.

With a view of science, it is appropriate to think of the non-excludability as the general attributes of knowledge – the inventor of a new "blueprint" can't prevent others from enjoying the benefits of this idea (the positive externality of knowledge spillover). But in an economic sense, it is more plausible to think of the idea as an economically useful knowledge that is largely excludable to competitors. That's because while the ideas by their nature may be freely accessible, intellectual property protection (patenting system) in the real-world economy is present to ensure the *de facto* excludability of innovation. In this case, the developed technologies should be specific to the needs and competencies of innovating sectors, and the knowledge created in one field of specialization tend to be poor substitutes for those in other – the sector-specific characteristic of economic knowledge.

Therefore, to combine the best features of both alternative specifications, I highlight the

[8] In explicit, knowledge is characterized as non-rival in the sense that the marginal costs for additional users are negligible. Intangible knowledge distinguishes from tangible physical factors input like physical capital that is fully rival and appropriable (Romer, 1990; Rosenberg, 1994).

central role of sector-specific purposeful R&D as well as the potential complement of external knowledge spillover from other sectors in the process of knowledge creation. A consistent framework can be formulated as follows:

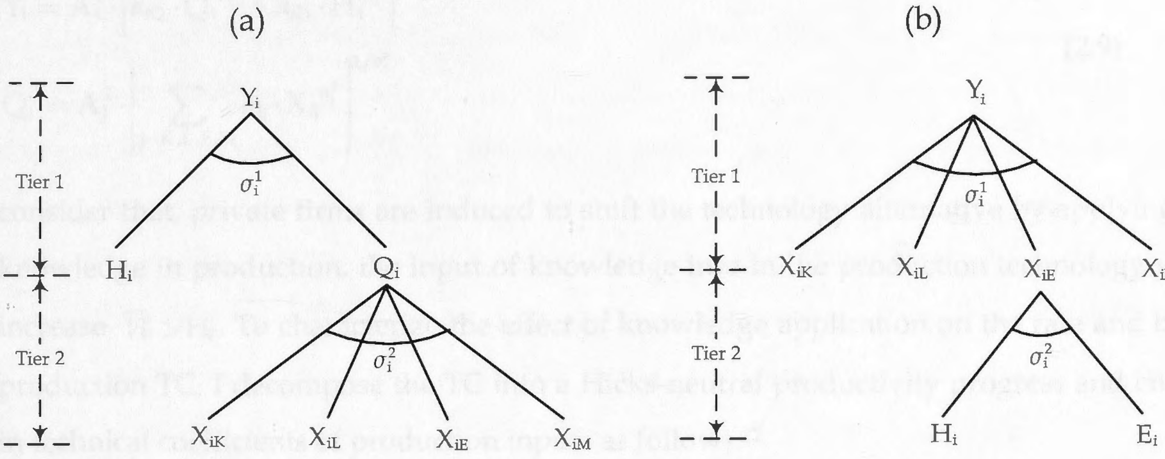
$$H_i(t+1) = R_i(t) + \gamma_i \cdot \left(\theta \cdot \sum_{j \neq i} R_j(t)\right) + (1-\delta) \cdot H_i(t) \qquad (2.8)$$

where Eq. (2.8) is an *innovation possibility frontier (IPF)* that describes the process of knowledge creation. That is, for any given sector i, the accumulation of its knowledge stock H_i is primarily driven by sector-specific purposeful R&D R_i. Knowledge spillovers resulting from R&D in other sectors $\sum_{j \neq i} R_j$ also contribute to knowledge accumulation in sector i. δ is the depreciation rate of knowledge obsolescence. γ_i is a fraction of knowledge in the public domain that can be assimilated by sector i, representing the sector's knowledge absorptive capacity. The degree to which knowledge created by one sector may spill over to the public pool accessible to other sectors is governed by θ, which denotes the externality of intersectoral R&D spillovers in the imperfect innovation market.[9]

The additive formulation of *IPF* implies that external R&D spillovers, corrected by local knowledge absorptive capacity, are a perfect substitute for in-house R&D. In particular, sector-specific purposeful R&D reflects the "no free rider" assumption: to gain economic benefits of innovation, firms should commit to undertake own R&D efforts and not free ride on external knowledge spillovers. Meanwhile, intersectoral R&D spillover reflects the "public good share" assumption: any sector can benefit from the positive externality of knowledge spillovers from innovation in other sectors through sectoral linkages along the supply chains (Popp, 2006; Clarke et al., 2008).

[9] The value of θ is determined by patent policy. A value of one means that the benefits of research can fully spill over to a public pool that is potentially available to all other sectors. A value of zero means that the benefits of research are exclusively appropriated by the innovating sector that undertakes research.

Figure 2.2: Alternative representations of production technology used in different industrial sectors



Note: (a) two-tier KLEM-H nested production technology used in conventional non-energy sectors, where knowledge H is used to combine with physical input composite Q. (b) two-tier KLM-EH nested production technology used in energy generation sectors, where knowledge H is used to combine with fossil energy E.

2.2.3 Production Technical Change

Upon understanding the process of knowledge creation, the next issue is to examine what's the effect of knowledge application on production TC. In nature, TC is a reconfiguration of production factors as an outcome of applying knowledge in production. Hence, an explicit representation of knowledge as a production input can give insights into its effect on TC.[10]

Consider a simple KLEM-H two-tier nested CES production technology.[11] As Fig. 2.2(a) shows, for a given sector i producing output Y_i, knowledge capital H_i substitutes for a composite of physical inputs Q_i, with the first-tier substitution parameter σ_i^1. The composite Q_i is in turn made up of physical capital X_{iK}, labor X_{iL}, energy X_{iE}, and

[10] The literature models the effect of knowledge application on TC through three routes: a direct impact on the carbon emission intensity (Nordhaus, 2002; Buonanno et al., 2003); a reduction in the mitigation cost function (Goulder and Mathai, 2000); knowledge substitution for physical inputs (Goulder and Schneider, 1999; Sue Wing, 2003; Popp, 2004).

[11] The KLEM-H production technology is commonly used in a CG modeling framework that explicitly represents multiple disaggregated physical inputs, where knowledge is treated as a general-purpose input combining with multiple physical inputs in production (Goulder and Schneider (1999), Sue Wing (2003), Otto et al. (2008),

material X_{iM}, with the second-tier substitution parameter σ_i^2:

$$
\begin{aligned}
Y_i &= A_i^1 \cdot \left[a_{iQ} \cdot Q_i^{\sigma_i^1} + a_{iH} \cdot H_i^{\sigma_i^1} \right]^{1/\sigma_i^1} \\
Q_i &= A_i^2 \cdot \left[\sum_{j=K,L,E,M} a_{ij} \cdot X_{ij}^{\sigma_i^2} \right]^{1/\sigma_i^2}
\end{aligned}
\tag{2.9}
$$

consider that, private firms are induced to shift the technology alternative by applying new knowledge in production, the input of knowledge into in the production technology would increase $\overline{H}_i > H_i$. To characterize the effect of knowledge application on the rate and bias of production TC, I decompose the TC into a Hicks-neutral productivity progress and changes in technical coefficients of production inputs as follows:[12]

$$
Y_i = A_i^1 \cdot \left[a_{iQ} \cdot Q_i^{\sigma_i^1} + a_{iH} \cdot \overline{H}_i^{\sigma_i^1} \right]^{1/\sigma_i^1} = \overline{A}_i^1 \cdot \left[\overline{a}_{iQ} \cdot Q_i^{\sigma_i^1} + \overline{a}_{iH} \cdot H_i^{\sigma_i^1} \right]^{1/\sigma_i^1}
$$

$$
\text{with} \quad \begin{cases}
\overline{A}_i^1 = A_i^1 \cdot \left[a_{iQ} + a_{iH} \cdot \left(\dfrac{\overline{H}_i}{H_i} \right)^{\sigma_i^1} \right]^{1/\sigma_i^1} & \Rightarrow \quad \overline{A}_i^1 > A_i^1 \\
\overline{a}_{iQ} = a_{iQ} \cdot \left(\dfrac{\overline{A}_i^1}{A_i^1} \right)^{-\sigma_i^1} & \Rightarrow \quad \overline{a}_{iQ} < a_{iQ} \\
\overline{a}_{iH} = a_{iH} \cdot \left(\dfrac{\overline{A}_i^1}{A_i^1} \right)^{-\sigma_i^1} \left(\dfrac{\overline{H}_i}{H_i} \right)^{\sigma_i^1} & \Rightarrow \quad \overline{a}_{iH} > a_{iH}
\end{cases}
\tag{2.10}
$$

where in the case of applying new knowledge in production $\overline{H}_i > H_i$, there is an increase in the Hicks-neutral productivity parameter $\overline{A}_i^1 > A_i^1$, implying an outward shift of *production possibility frontier* and factor productivity growth (the rate of production TC). Meanwhile, there is also a uniform reduction in the technical coefficient of each physical input $\overline{a}_{ij} < a_{ij}$ $(j = K, L, E, M)$ and a rise in the technical coefficient of knowledge $\overline{a}_{iH} > a_{iH}$.[13] It suggests a decline in the cost share of physical inputs and a rise of knowledge (the bias of production

---

[12] For the details of decomposition of TC, see Appendix 2.B.

[13] Knowledge and physical inputs are gross substitutes with an elasticity of substitution $s_i^1 > 1$, which translates into the CES substitution parameter $\sigma_i^1 = (s_i^1 - 1)/s_i^1 > 0$, we hence have $\overline{a}_{iQ} < a_{iQ}$. Given that the cost share of each physical input at the second tier remains unchanged, a reduction in the cost share of physical composite at the first tier will eventually lead to a uniform reduction in the cost share of each physical input $\overline{a}_{ij} < a_{ij}$ $(j = K, L, E, M)$. Using constraint on the technical coefficients of inputs $\sum_j \overline{a}_{ij} + \overline{a}_{iH} = \sum_j a_{ij} + a_{iH} = 1$, we have $\overline{a}_{iH} > a_{iH}$ given $\overline{a}_{ij} < a_{ij}$.

TC). Therefore, the effect of knowledge application on TC can be characterized as knowledge substitution for physical inputs with a uniform saving of them.

In general, the above conclusions hold for conventional production sectors, but it may not apply to fossil energy sectors. That's because creating energy-related knowledge is more relevant to innovation and TC in fossil energy sectors, where the energy-related knowledge is normally embedded in specific fossil energy to embody the purpose of energy efficiency improvement. This differs from the general-purpose knowledge that can be combined with various physical inputs as the case in conventional production sectors. Fig. 2.2(b) illustrates the case of fossil energy sectors, where the input of knowledge is only used to combine fossil energy rather than all physical inputs. This alteration enables more energy services to be supplied with the same quantities of physical fossil energy.[14] In that case, the production function in Eq. (2.9) becomes a different two-tier nested CES structure as:

$$\begin{aligned} & \mathrm{Y_i} = \mathrm{A_i^1} \cdot \left[\sum_{j=K,L,M} a_{ij} \cdot \mathrm{X_{ij}}^{\sigma_i^1} + a_{iEH} \cdot \mathrm{X_{iEH}}^{\sigma_i^1} \right]^{1/\sigma_i^1} \\ & \mathrm{X_{iEH}} = \mathrm{A_i^2} \cdot \left[a_{iE} \cdot \mathrm{E_i}^{\sigma_i^2} + a_{iH} \cdot \mathrm{H_i}^{\sigma_i^2} \right]^{1/\sigma_i^2} \end{aligned} \tag{2.11}$$

where in the first-tier KLEM combination, $\mathrm{X_{iEH}}$ represents the knowledge-embodied energy inputs rather than physical fossil energy. At the second tier, $\mathrm{X_{iEH}}$ is a CES aggregate of physical fossil energy $\mathrm{E_i}$ and energy-related knowledge $\mathrm{H_i}$. I firstly capture the effect of knowledge application on the second-tier production function as:

$$\begin{aligned} & \overline{\mathrm{X}}_{\mathrm{iEH}} = \mathrm{A_i^2} \cdot \left[a_{iE} \cdot \mathrm{E_i}^{\sigma_i^2} + a_{iH} \cdot \overline{\mathrm{H}}_\mathrm{i}^{\sigma_i^2} \right]^{1/\sigma_i^2} = \overline{\mathrm{A_i^2}} \cdot \left[\overline{a}_{iE} \cdot \mathrm{E_i}^{\sigma_i^2} + \overline{a}_{iH} \cdot \mathrm{H_i}^{\sigma_i^2} \right]^{1/\sigma_i^2} \\ & \text{with} \begin{cases} \overline{\mathrm{A_i^2}} = \mathrm{A_i^2} \cdot \left[a_{iE} + a_{iH} \cdot \left(\dfrac{\overline{\mathrm{H}}_\mathrm{i}}{\mathrm{H_i}} \right)^{\sigma_i^2} \right]^{1/\sigma_i^2} & \Rightarrow \quad \overline{\mathrm{A_i^2}} > \mathrm{A_i^2} \\ \overline{a}_{iE} = a_{iE} \cdot \left(\dfrac{\overline{\mathrm{A_i^2}}}{\mathrm{A_i^2}} \right)^{-\sigma_i^2} & \Rightarrow \quad \overline{a}_{iE} < a_{iE} \\ \overline{a}_{iH} = a_{iH} \cdot \left(\dfrac{\overline{\mathrm{A_i^2}}}{\mathrm{A_i^2}} \right)^{-\sigma_i^2} \cdot \left(\dfrac{\overline{\mathrm{H}}_\mathrm{i}}{\mathrm{H_i}} \right)^{\sigma_i^2} & \Rightarrow \quad \overline{a}_{iH} > a_{iH} \end{cases} \end{aligned} \tag{2.12}$$

[14] The KLM-EH structure is mostly applied in Ramsey growth models (e.g., WITCH, DICE). For example, Popp, (2004) models the effective inputs of energy as a CES aggregate of fossil fuels and energy-related knowledge.

where in the case of applying new knowledge, there is a reduction in the technical coefficient of physical fossil energy $\overline{a}_{iE} < a_{iE}$ and a rise for knowledge input $\overline{a}_{iH} > a_{iH}$. This effect then transmits into the first-tier production function, raising the inputs of knowledge-embodied energy $\overline{X}_{iEH} > X_{iEH}$. Hence, TC is characterized as changes in both Hicks-neutral parameter $\overline{A_i^1}$ and technical coefficients of production inputs $\overline{a}_{ij}$ $(j = K, L, M)$, $\overline{a}_{iEH}$:

$$Y_i = A_i^1 \cdot \left[\sum_{j=K,L,M} a_{ij} \cdot X_{ij}^{\sigma_i^1} + a_{iEH} \cdot X_{iEH}^{\sigma_i^1} \right]^{1/\sigma_i^1} = \overline{A_i^1} \cdot \left[\sum_{j=K,L,M} \overline{a}_{ij} \cdot X_{ij}^{\sigma_i^1} + \overline{a}_{iEH} \cdot X_{iEH}^{\sigma_i^1} \right]^{1/\sigma_i^1}$$

$$\text{with} \begin{cases} \overline{A_i^1} = A_i^1 \cdot \left[\sum_{j=K,L,M} a_{ij} + a_{iEH} \cdot \left(\dfrac{\overline{X}_{iEH}}{X_{iEH}} \right)^{\sigma_i^1} \right]^{1/\sigma_i^1} & \Rightarrow \quad \overline{A_i^1} > A_i^1 \\ \overline{a}_{ij} = a_{ij} \cdot \left(\dfrac{\overline{A_i^1}}{A_i^1} \right)^{-\sigma_i^1} & \Rightarrow \quad \overline{a}_{ij} < a_{ij} \\ \overline{a}_{iEH} = a_{iEH} \cdot \left(\dfrac{\overline{A_i^1}}{A_i^1} \right)^{-\sigma_i^1} \cdot \left(\dfrac{\overline{X}_{iEH}}{X_{iEH}} \right)^{\sigma_i^1} & \Rightarrow \quad \overline{a}_{iEH} > a_{iEH} \end{cases} \tag{2.13}$$

where applications of new knowledge would eventually lead to a higher total factor productivity $\overline{A_i^1} > A_i^1$ (the rate of production TC). In addition, there is a uniform reduction in the cost share of capital, labor, and materials $\overline{a}_{ij} < a_{ij}$ $(j = K, L, M)$ and a rise for the knowledge-embodied energy input $\overline{a}_{iEH} > a_{iEH}$ (the bias of production TC).

Therefore, it is found that knowledge application in energy sector can create total factor productivity growth and lower cost shares of non-energy physical inputs (e.g., capital, labor and materials) – the same as in conventional non-energy production sectors. The difference, however, lies in whether there is an energy-saving effect (a reduction in the cost share of physical fossil energy input). To investigate this issue, I use Eq. (2.12) and Eq. (2.13) to describe the cost share of fossil energy input as:

$$\frac{\overline{a}_{iEH} \cdot \overline{a}_{iE}}{a_{iEH} \cdot a_{iE}} = \underbrace{\left(\frac{\overline{A_i^1}}{A_i^1} \right)^{-\sigma_i^1} \left(\frac{\overline{X}_{iEH}}{X_{iEH}} \right)^{\sigma_i^1}}_{>1} \underbrace{\left(\frac{\overline{A_i^2}}{A_i^2} \right)^{-\sigma_i^2}}_{<1} \tag{2.14}$$

where the cost share of fossil energy is a product of the cost share of knowledge-embodied energy $\overline{a}_{iEH}$ (at first tier) and that of physical fossil energy $\overline{a}_{iE}$ (at second tier). As Eq. (2.14) shows, the energy-saving effect of knowledge application depends on a variety of factors, not necessarily implying a reduction in the cost share of fossil energy input. Therefore, the general conclusion about the energy-saving effect of knowledge application may not always hold across sectors within an economy. For example, development of extraction and drilling technologies in oil and natural gas industries actually requires more inputs of fossil energy to complement the use of these new technologies, without an energy-saving effect. Therefore, different production technologies (e.g., how knowledge substitute for physical inputs) used in different sectors may generate a diverging effect on carbon savings from applying new technologies.[15]

Moreover, the previous analysis on TC is within a single-sector framework. However, in realistic models where the supply side of an economy consists of multiple sectors, TC in a given sector should depend on not only knowledge substitution for physical inputs within this sector, but also the general equilibrium effect of cross-sector knowledge interactions. Therefore, to faithfully represent the intersectoral knowledge interaction and its effect on TC, I should develop a disaggregated framework that explicitly considers multiple production sectors.

2.3 Implications for Multi-sector Modeling

So far the mechanism of endogenous TC has been analyzed in a single-sector partial equilibrium framework, which consists of three consecutive processes: R&D inducement, knowledge creation, and production TC. In this section, I aim to provide methodological guidance on how to incorporate these three processes into a multi-sector CGE framework.

As shown in the area (I) in Fig. 2.3, the supply side of an economy has been extended to multiple disaggregated production sectors. For the representative firm in each individual sector, it would undertake purposeful R&D investment as an inventive response to input price changes in pursuit of profit maximization (microeconomic foundation of innovation). Hence, the decision problem facing private firms is to optimally choose various production

[15] Some empirical studies also reach such a finding. For example, Baker et al. (2008) argue that different representations of technology lead to different results in terms of the effect of TC on the marginal abatement cost (MAC) of carbon emission. Under certain conditions it is possible for knowledge application to increase the MAC. van der Werf (2008) also find the evidence that different nesting structures of production function may generate diverging effects of TC on the cost of climate policies.

inputs for profit maximization.[16] By solving the problem of profit maximization, interactions among the four effects associated with R&D inducement (see Section 2.2.1) can be captured. The induced R&D investment accumulates the stock of knowledge according to the *innovation possibility frontier* (see Section 2.2.2). In the area (II), within the disaggregated CGE framework that represents multi-sector economic transactions and linkage along the supply chains, a portion of outputs produced by conventional production sectors will be used (as intermediate inputs) by a R&D sector. The R&D sector then produces and supplies raw R&D goods to satisfy the demand for R&D good by conventional production sectors for knowledge accumulation.[17]

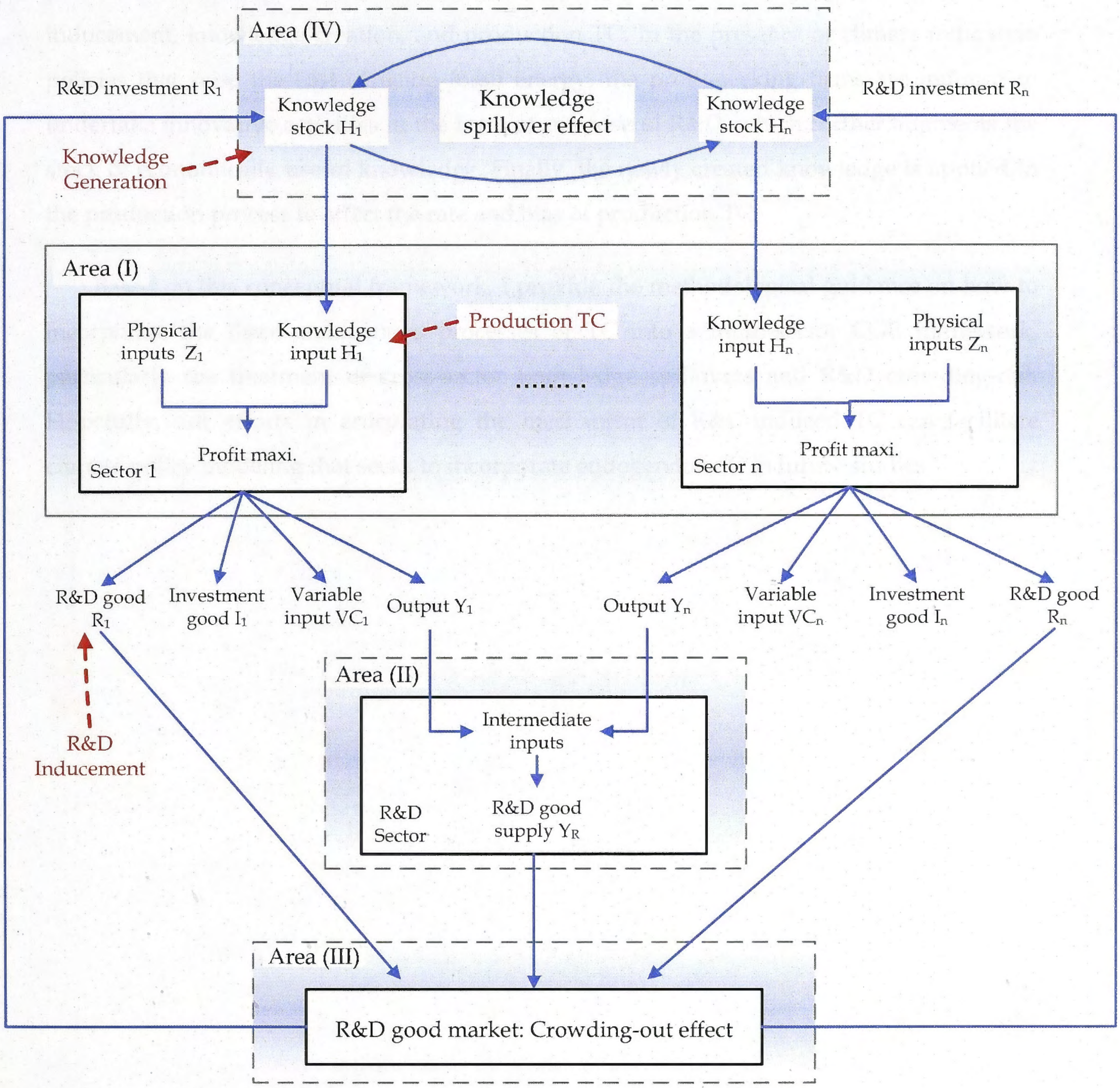
In the area (III), the demand and supply interacts in the market of R&D good, which determines the equilibrium level of R&D resources allocated across sectors. In general, the crowding-out effect may occur in the R&D market, where climate mitigation policies that induce energy-related R&D may reduce the availability of R&D resources in other sectors of the economy, potentially driving down aggregate economic outputs. This implies that the opportunity cost of carbon abatement may be higher with the inclusion of R&D-induced TC, rather than presumptively leading to lower abatement costs (e.g., Goulder and Schneider, 1999; Nordhaus, 2002; Popp, 2004; Pizer and Popp, 2008). In the area (IV), the knowledge stock specific to each individual sector is augmented by the R&D goods invested in that sector, combined with the potential complement of R&D spillovers from other sectors in the economy (positive externality of technology spillover).

Accordingly, the three endogenous processes of TC can be located in the Fig. 2.3. First, R&D inducement results from the inventive response of private firms to input price changes for avoiding higher cost burdens. Second, knowledge creation emanates from sector-specific purposeful R&D and intersectoral knowledge spillovers. Third, production TC is due to applications of knowledge in a production process, with an outcome of shifting out *production possibility frontier* and substituting knowledge for costly physical inputs.

[16] As compared to myopic recursive-dynamic framework (Sue Wing, 2003), an intertemporal model appears better suited to representing the problem of intertemporal profit maximization (Goulder and Schneider, 1999; Otto et al., 2008; Loschel and Otto, 2009).

[17] Provided that a portion of produced goods are consumed for R&D, this treatment reflects a trade-off between output production and knowledge generation, which provides an avenue to explore whether there is substitutability or complementarity between conventional production and innovation activities (Gillingham et al., 2008).

Figure 2.3: Incorporating the endogenous mechanism of R&D-induced TC into a multi-sector general equilibrium modeling framework.



Note: Three endogenous processes underlying TC are highlighted by red arrows. 1) R&D inducement results from the inventive response of private firms to input price changes in pursuit of economic profitability; 2) Knowledge creations are driven by sector-specific purposeful R&D investment and intersectoral knowledge spillovers; 3) Production TC is due to the applications of augmented knowledge asset in a production process.

2.4 Conclusions

This chapter revisits the mechanism of endogenous TC for climate change mitigation by providing a conceptual framework that captures three underlying processes: R&D inducement, knowledge creation, and production TC. In the presence of climate mitigation policies that raise the cost of using fossil energy, the profit-seeking firms are induced to undertake innovative activities in the form of purposeful R&D, which further augments the stock of economically useful knowledge. Finally, the newly created knowledge is applied in the production process to affect the rate and bias of production TC.

Based on this conceptual framework, I provide the methodological guidance on how to incorporate the three endogenous processes of TC into a multi-sector CGE framework, particularly the treatment of cross-sector knowledge spillovers and R&D crowding-out. Hopefully, our efforts in articulating the mechanism of R&D-induced TC can facilitate climate policy modeling that seeks to incorporate endogenous TC in future studies.

Appendix to Chapter 2

2.A Derivation of R&D inducement by raising fossil energy price

For the implicit function Eq. (2.4), taking a derivative with respect to P_E, I capture the response of R&D investment to fossil energy price changes as:

$$R = D(P)\cdot(P-\lambda\cdot MC) = \Phi(\lambda, MC, P, D)$$
$$\Rightarrow \frac{\partial R}{\partial P_E} = \frac{\partial \Phi}{\partial \lambda}\cdot\frac{\partial \lambda}{\partial P_E} + \frac{\partial \Phi}{\partial MC}\cdot\frac{\partial MC}{\partial P_E} + \frac{\partial \Phi}{\partial P}\cdot\frac{\partial P}{\partial P_E} + \frac{\partial \Phi}{\partial D}\cdot\frac{\partial D}{\partial P_E} \tag{2.A.1}$$

Recall that, reductions in marginal cost of production depend on R&D investment $\lambda = \lambda(R)$, and market demand satisfies a downward-sloping curve $D = D(P)$, I hence capture the responses of both variables to energy price changes P_E as:

$$\frac{\partial \lambda}{\partial P_E} = \frac{\partial \lambda}{\partial R}\cdot\frac{\partial R}{\partial P_E} \qquad \frac{\partial D}{\partial P_E} = \frac{\partial D}{\partial P}\cdot\frac{\partial P}{\partial P_E} \tag{2.A.2}$$

Substitute (2.A.2) into (2.A.1) and yield Eq. (2.5) as follows:

$$\frac{\partial R}{\partial P_E}\cdot\left(1-\frac{\partial \Phi}{\partial \lambda}\cdot\frac{\partial \lambda}{\partial R}\right) = \frac{\partial \Phi}{\partial MC}\cdot\frac{\partial MC}{\partial P_E} + \frac{\partial \Phi}{\partial P}\cdot\frac{\partial P}{\partial P_E} + \frac{\partial \Phi}{\partial D}\cdot\frac{\partial D}{\partial P_E}$$

$$\begin{aligned}\Rightarrow \frac{\partial R}{\partial P_E} &= \left(\frac{\partial \Phi}{\partial MC}\cdot\frac{\partial MC}{\partial P_E} + \frac{\partial \Phi}{\partial P}\cdot\frac{\partial P}{\partial P_E} + \frac{\partial \Phi}{\partial D}\cdot\frac{\partial D}{\partial P_E}\right)\cdot\left(1-\frac{\partial \Phi}{\partial \lambda}\cdot\frac{\partial \lambda}{\partial R}\right)^{-1} \\ &= \left(\frac{\partial \Phi}{\partial MC}\cdot\frac{\partial MC}{\partial P_E} + \frac{\partial \Phi}{\partial P}\cdot\frac{\partial P}{\partial P_E} + \frac{\partial \Phi}{\partial D}\cdot\frac{\partial D}{\partial P}\cdot\frac{\partial P}{\partial P_E}\right)\cdot\left(1-\frac{\partial \Phi}{\partial \lambda}\cdot\frac{\partial \lambda}{\partial R}\right)^{-1} \\ &= \left(\frac{\partial \Phi}{\partial MC}\cdot\frac{\partial MC}{\partial P_E} + \frac{\partial \Phi}{\partial P}\cdot\frac{\partial P}{\partial P_E} + \frac{\partial \Phi}{\partial D}\cdot\frac{\partial D}{\partial P}\cdot\frac{\partial P}{\partial P_E}\right)\cdot\left(1+\frac{\partial \Phi}{\partial \lambda}\cdot\frac{\lambda}{R}\cdot\xi_R\right)^{-1}\end{aligned} \tag{2.A.3}$$

■

2.B Decomposition of produciton technical change

$$
\begin{aligned}
\overline{Y}_i &= A_i^1 \cdot \left[a_{iQ} \cdot Q_i^{\sigma_i^1} + a_{iH} \cdot \overline{H}_i^{\sigma_i^1} \right]^{1/\sigma_i^1} \\
&= A_i^1 \cdot \left[a_{iQ} \cdot Q_i^{\sigma_i^1} + a_{iH} \cdot \left(\frac{\overline{H}_i}{H_i} \right)^{\sigma_i^1} \cdot H_i^{\sigma_i^1} \right]^{1/\sigma_i^1} \\
&= A_i^1 \cdot \left[a_{iQ} + a_{iH} \cdot \left(\frac{\overline{H}_i}{H_i} \right)^{\sigma_i^1} \right]^{1/\sigma_i^1} \cdot \left[\frac{a_{iQ} \cdot Q_i^{\sigma_i^1}}{a_{iQ} + a_{iH} \cdot \left(\frac{\overline{H}_i}{H_i} \right)^{\sigma_i^1}} + \frac{a_{iH} \cdot \left(\frac{\overline{H}_i}{H_i} \right)^{\sigma_i^1} \cdot H_i^{\sigma_i^1}}{a_{iQ} + a_{iH} \cdot \left(\frac{\overline{H}_i}{H_i} \right)^{\sigma_i^1}} \right]^{1/\sigma_i^1}
\end{aligned}
\tag{2.B.1}
$$

Define the new Hicks-neutral productivity parameter as follows:

$$
\overline{A_i^1} = A_i^1 \cdot \left[a_{iQ} + a_{iH} \cdot \left(\frac{\overline{H}_i}{H_i} \right)^{\sigma_i^1} \right]^{1/\sigma_i^1} \quad \Rightarrow \quad a_{iQ} + a_{iH} \cdot \left(\frac{\overline{H}_i}{H_i} \right)^{\sigma_i^1} = \left(\frac{\overline{A_i^1}}{A_i^1} \right)^{\sigma_i^1}
\tag{2.B.2}
$$

Substitute (2.B.2) into the last expression in (2.B.1) and yields:

$$
\begin{aligned}
\overline{Y}_i &= \overline{A_i^1} \cdot \left[\frac{a_{iQ} \cdot Q_i^{\sigma_i^1}}{\left(\frac{\overline{A_i^1}}{A_i^1} \right)^{\sigma_i^1}} + \frac{a_{iH} \cdot \left(\frac{\overline{H}_i}{H_i} \right)^{\sigma_i^1} \cdot H_i^{\sigma_i^1}}{\left(\frac{\overline{A_i^1}}{A_i^1} \right)^{\sigma_i^1}} \right]^{1/\sigma_i^1} \\
&= \overline{A_i^1} \cdot \left[a_{iQ} \cdot \left(\frac{\overline{A_i^1}}{A_i^1} \right)^{-\sigma_i^1} \cdot Q_i^{\sigma_i^1} + a_{iH} \cdot \left(\frac{\overline{A_i^1}}{A_i^1} \right)^{-\sigma_i^1} \cdot \left(\frac{\overline{H}_i}{H_i} \right)^{\sigma_i^1} \cdot H_i^{\sigma_i^1} \right]^{1/\sigma_i^1} \\
&= \overline{A_i^1} \cdot \left[\overline{a}_{iQ} \cdot Q_i^{\sigma_i^1} + \overline{a}_{iH} \cdot H_i^{\sigma_i^1} \right]^{1/\sigma_i^1}
\end{aligned}
\tag{2.B.3}
$$

where new technical coefficients become $\overline{a}_{iQ} = a_{iQ} \cdot \left(\overline{A_i^1} / A_i^1 \right)^{-\sigma_i^1}$ for physical inputs composite and $\overline{a}_{iH} = a_{iH} \cdot \left(\overline{A_i^1} / A_i^1 \right)^{-\sigma_i^1} \cdot \left(\overline{H}_i / H_i \right)^{\sigma_i^1}$ for knowledge input.

■

Chapter 3

Can Technological Innovation Help China Take on Its Climate Responsibility? A Computable General Equilibrium Analysis[*]

Abstract: This chapter examines the effectiveness of China's indigenous R&D investment and technological innovation to curb its carbon emissions. The mechanism of endogenous technical change (TC) is incorporated into an intertemporal computable general equilibrium (CGE) model. R&D investments and knowledge creations are modeled as the endogenous behaviors of private firms. The accumulated stocks of knowledge are applied in the production process to affect the rate and bias of TC. Simulation results show that: 1) While indigenous R&D play a significant role to curb carbon emissions, sole dependence on R&D may be far from sufficient to achieve China's pledged Copenhagen climate target, with complementary policies required to reinforce existing private R&D efforts; 2) Innovation policies including public R&D subsidy and intellectual property right protection can help strengthen economy-wide R&D investment and reduce emissions, but this complementary effect is still minor and insufficient to meet the stipulated emission cuts target; 3) Carbon taxation can create significant carbon-saving benefits and fulfill the pledged climate target, but this achievement is at the cost of economic losses. The induced technical improvement, however, can partially mitigate the deadweight losses incurred by carbon tax distortion.

Keywords: CGE Model, Endogenous Technical Change, R&D, Climate Policy, China

[*] This chapter is based on the paper published in Energy Policy as Jin, W. (2012). "Can technological innovation help China take on its climate responsibility? An intertemporal general equilibrium analysis," vol. 49, 629-641.

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3.1 Introduction

Since launching the "open-door" policy in the late 1970s, China has experienced a profound transformation from a rural agricultural-based to an urban industrial-focused society. As one of the fastest growing economies, China is expected to continue its growth path and overtake the U.S. to become the world's largest economy by 2030 (World Bank, 2011). While rapid economic growth has created tremendous wealth and prosperity, China's development pattern, with enormous resource depletion and environmental degradation, is becoming unsustainable, putting this country at the center of international debates on energy governance and climate mitigation (IEA, 2010; EIA, 2010).

While a country's economic size generally reflects its energy demand and carbon emissions, China's appetite for energy and emission is unsurprisingly mammoth. During the period 1990-2005, China's total primary energy demand grew by 4.7% annually from 874 to 1742 Mtoe, and its CO_2 emissions grew by 5.6% per year from 2244 to 5101 Mt (IEA, 2007). In a global context, China had overtaken the U.S. in 2010 to become the world's largest carbon emitter, and its emission levels will continue to rise rapidly in line with its industrialization and urbanization (IEA, 2010; BP, 2011). Without a significant policy regulation, this growth trend is likely to offset climate mitigation efforts elsewhere. In the global collective efforts of tackling climate change, there is no disagreement that China needs to take on a growing responsibility of carbon abatement.

To stabilize the rising emission trend, China would have set a daunting challenge of cutting its carbon intensity given a large demographic base and rapidly rising consumption levels (Kaya, 1990; IPCC, 2000). In the minds of the leadership in Beijing, the key to handling this challenge is to decouple carbon emissions from economic growth through technological innovation. This is true for China where the growth story, beyond global manufacturing engine, is increasingly about innovation. In the course of building a "harmonious society" through "scientific development", Beijing has begun to raise awareness of the pivotal role that technological innovation plays in sustaining long-term quality and sustainable growth.[1]

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[1] This is reflected by a commitment to create an "innovation-oriented" society made by Chinese President Hu at the National Science and Technology Conference in January 2006, an occasion which also saw the unveiling of the 2006-2020 Medium to Long-term Plan for the Development of Science and Technology (MOST, 2006b).

In a changing landscape of global innovation, the emergence of innovation hubs in China is underpinned by the strong growth of R&D investments in indigenous innovation. While the U.S. and Japan remain leaders in science and technology innovation, they face increasing competition from emerging markets, notably China - the world's third leading R&D investor at $100 billion in 2010 (OECD, 2010).[2] In a transition to an innovation-oriented society, Beijing is expected to boost future investments in indigenous innovation. This is reflected by the government's spending target of 2.5% of GDP on R&D by 2020, translating into a tripling of R&D investment over the next decade to $300 billion (MOST, 2006b).

In a context where climate change mitigation and technological innovation are closely interconnected, it is vital to investigate the effectiveness of China's indigenous R&D efforts to achieve its carbon reduction commitment. I thus aim to address the following four issues: 1) How substantially can R&D investment and TC reduce China's carbon emissions; 2) Can these emission cuts driven by R&D guarantee the achievement of Beijing's pledged climate target; 3) Do innovation policies like public R&D subsidies provide significant aids to enhance innovation and cut carbon emissions; 4) Is it necessary to introduce climate policies to complement innovation policy to achieve the pledged climate target.

To handle these issues, I put the mechanism of R&D-induced TC into a multi-sector CGE model. The theory of R&D-induced TC has its origins in the second-generation endogenous growth literature, which highlights the role of R&D and knowledge in boosting technology progress and endogenous growth (Romer, 1990; Aghion and Howitt, 1998; Acemoglu, 2009a; Heutel and Fischer, 2013). In climate policy analysis, the mechanism of R&D-induced TC is also adopted to represent the endogenous process of TC (Nordhaus, 2002; Popp, 2004; Sue Wing, 2006; Bosetti et al., 2008; Acemoglu et al., 2009b). In particular, within a CGE framework, the representation of disaggregated sectors provides a useful platform to examine the general equilibrium effect of intersectoral knowledge interactions, including cross-sector knowledge spillover and R&D crowding-out, which have a significant impact on the timing and costs of carbon abatement (Löschel, 2002; Popp, 2006; Clarke et al., 2006, 2008; Gillingham, 2008).

[2] R&D spending in China grew by about 20% per year over the last decade. Average R&D investments in G7 markets, by comparison, have grown by 3.2% annually during the same period. R&D intensity remained flat across G7 markets over the past decade at 2.1%. In China it has double as a share of GDP since 1999, reaching 1.5%, leaving room for potential improvement by international standards (OECD, 2008, 2010).

To our knowledge, few CGE studies that feature the R&D-induced TC have appeared in climate policy literature. Goulder and Schneider (1999) investigate the attractiveness of the U.S. climate policies in the presence of induced TC. Sue Wing (2003) examines the impact of induced TC on the U.S. macroeconomic cost of carbon taxation. Wang et al. (2009) analyze the role that TC could play in designing China's climate mitigation targets. Bye and Jacobsen (2011) scrutinize differentiated R&D subsidies across general and carbon-saving TC and its impacts on the Norwegian economic cost of carbon tax. Investigations of R&D-induced TC also include studies that model interactions between R&D subsidies and carbon constraints in the presence of technological externality by Otto et al. (2007), Otto et al. (2008), Otto and Reilly (2008), and Löschel and Otto (2009).

As a needed complement to the existing literature, this paper contributes to advancing modeling methods in the following ways: 1) Instead of using recursive-dynamic modeling, I develop an intertemporal optimization framework for incorporating more macroeconomic elements into the micro-founded CGE core;[3] 2) I fully represent the mechanism of R&D-induced TC within a multi-sector CGE structure, with special treatments on innovation externalities including R&D crowding-out, intersectoral knowledge spillovers, and the dual faces of R&D in knowledge absorption.

The paper is organized as follows: Section 3.2 provides a detailed description of modeling framework. Section 3.3 discusses model implementation, with an emphasis on knowledge accounting for calibrating a model with R&D-induced TC. Simulation results and discussions under various scenarios are presented in Section 3.4. Section 3.5 concludes.

3.2 Model Description

3.2.1 Basic Framework

Fossil energy is an indispensable input into every industry in the Chinese economy. A model

[3] This differs from recursive-dynamic models that solve for a sequence of static equilibrium in a Slow-Swan formulation, where capital accumulation is based on an exogenous saving rate with myopic expectations. In contrast, optimization models endogenize the intertemporal behavior of economic agents, with current decisions depending on expectation about future economic prospect (Jorgenson and Wilcoxen, 1990; Bovenberg and Goulder, 1996; McKibbin and Wilcoxen, 1999; Dixon et al., 2005). As modern macroeconomic elements (e.g., expectation, assets) play an important role in China's market-oriented economt, intertemporal modeling frameworks that incorporate macroeconomic elements are more applicable to our study for China.

encompassing multiple industries and commodities is thus required to capture the full general equilibrium effect of policy shocks.[4] In this model framework, the Chinese economy is represented by multiple economic agents, including: Twelve production sectors, an investment (producing physical capital goods), a R&D sector (producing R&D goods), a representative household, and a government. To be relevant to climate policy analysis, the twelve production sectors consists of five energy sectors and seven non-energy sectors.[5] Carbon emissions are calculated based on carbon intensities of fossil fuel inputs (coal, oil and natural gas) in intermediate production and final use.

In the spirit of the G-Cubed model (McKibbin and Wilcoxen, 1999),[6] our modeling framework describes the economic behaviors of multiple agents within a general equilibrium structure, which outlines the input-output (IO) circular flows of commodities and primary factor inputs within an economy (see Fig. 3.1). There are 12 commodities and corresponding production sectors, indexed by the row subscript j $(j=1,2,\ldots,12)$ and the column subscript i $(i=1,2,\ldots,12)$; 3 types of primary factors (labor, physical capital, knowledge capital), indexed by the subscript f $(f=L,K,H)$; 5 types of final uses (consumption, investment, R&D, government, export), indexed by the subscript d $(d=C,I,R,G,X)$. Intersectoral interactions in intermediate production transaction are represented by the $j \times i$ matrix $\mathbf{X}$; Inputs of primary factors into production are indicated by the $f \times i$ matrix $\mathbf{V}$; Final uses of produced commodities are represented by the $j \times d$ matrix $\mathbf{G}$.

To develop a numerical model, I describe the decision problems of economic agents and characterize their economic behavior in a decentralized equilibrium.[7] To represent the mechanism of R&D-induced TC, I extend the traditional framework by incorporating R&D investment and knowledge input. This will be articulated in the following section.

[4] The multi-sector specification differs from Ramsey growth model where the supply side of an economy is represented as a single producer of unique final goods. The economic dynamics are captured by a social planner choosing the optimal level of inputs into an aggregate production function, e.g., R&DICE (Nordhaus, 2002), ENTICE (Popp, 2004), and WITCH (Bosetti et al., 2008).
[5] For the model sectoral classification and mapping by reference to the GTAP, see Appendix 3.A.
[6] The G-Cubed model introduces macroeconomic elements into micro-founded CGEframework. including: interactions between real and financial sides; intertemporal dynamics of physical asset; the neoclassical optimizing and liquidity-constrained behavior of consumers; imperfect capital mobility and adjustment costs; intertemporal equilibrium with rational expectation.
[7] A thorough description of the specification and characterization of the decision problem faced by each economic agent are provided in Appendix 3.B.

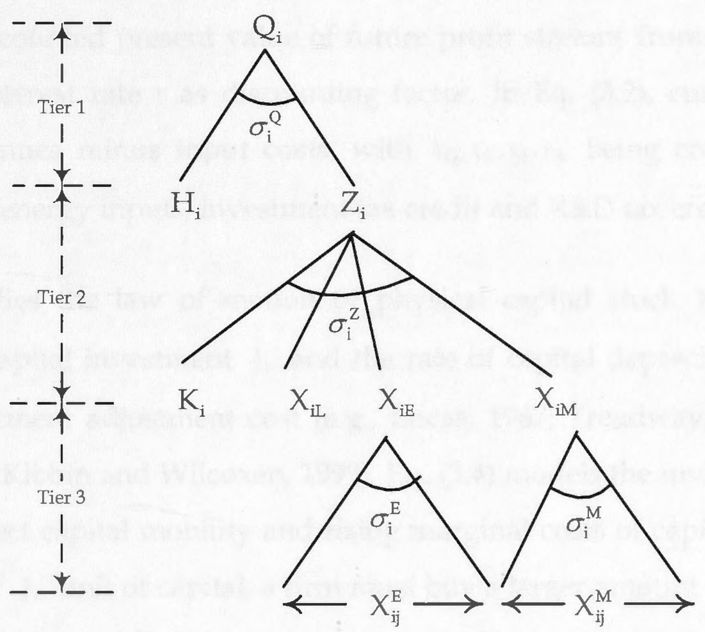
Figure 3.1: Input-output circular flows of commodities and primary factors within an economy, with an explicit representation of R&D investment (R) as a final use category and knowledge inputs (H) as a primary factor input

		Industries i						Final Demand d					Total Output
		1	.	.	i	.	12	C	I	G	R	X	
Commodities j	1	$x_{1,1}$	.	.	$x_{1,i}$	.	$x_{1,12}$	C_1	I_1	G_1	R_1	X_1	Y_1
	.	.	.	.	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.	.	.	.	.
	j	$x_{j,1}$	.	.	$x_{j,i}$	.	$x_{j,12}$	C_j	I_j	G_j	R_j	X_j	Y_j
	.	.	.	.	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.	.	.	.	.
	12	$x_{12,1}$	.	.	$x_{12,i}$	.	$x_{12,12}$	C_{12}	I_{12}	G_{12}	R_{12}	X_{12}	Y_{12}
Primary Factor f	K	K_1	.	.	K_i	.	K_{12}						
	L	L_1	.	.	L_i	.	L_{12}						
	H	H_1	.	.	H_i	.	H_{12}						
Imports	M	M_1	.	.	M_i	.	M_{12}						
Total Outlays		Y_1	.	.	Y_i	.	Y_{12}						

3.2.2 Endogenous Technical Change

TC in itself is a reconfiguration of productive factors as an outcome of applying new knowledge (e.g., technique, know-how, managerial skills) into a production process, thus a representation of intangible knowledge asset as a production input can give insights into its effect on production TC (Goulder and Schneider, 1999; Sue Wing, 2006; Bosetti et al., 2008). In this direction, our model incorporates the mechanism of R&D-induced TC. That is, R&D investments are modeled as endogenous behaviors of profit-seeking private firms, which augment the economically useful stock of knowledge. The accumulated stocks of knowledge are then applied in a production process to facilitate a reconfiguration of production inputs for productivity growth (the rate of production TC). Simultaneously, the use of knowledge inputs leads to a substitution for physical inputs such as labor, energy and materials (the bias of production TC).

Figure 3.2: KLEM-H three-tier nested CES technology in production sectors



To model the mechanism, we specify the production technology as a separable KLEM-H nested CES function. As Fig. 3.2 shows, for any given sector i producing output Q_i, knowledge capital H_i substitutes for the composite of physical inputs Z_i, which is in turn made up of primary factor inputs of physical capital K_i and labor X_{iL}, as well as intermediate inputs of energy bundle X_{iE} and material bundle X_{iM}. X_{iE} comprises five energy goods X_{ij}^E, and X_{iM} is composed of seven non-energy goods X_{ij}^M. Given this production technology, the producer problem in each individual sector i is formulated as:

$$\max \quad V_i(t) = \int_t^{\infty} \exp\left[-\int_t^s r(s')\cdot ds'\right]\cdot \Pi_i(s)\cdot ds \tag{3.1}$$

$$\text{s.t.} \quad \Pi_i(t) = (1-\tau_Q)\cdot[P_i(t)\cdot Q_i(t) - P_{iL}(t)\cdot X_{iL}(t) - (1+\tau_C)\cdot P_{iE}(t)\cdot X_{iE}(t) - P_{iM}(t)\cdot X_{iM}(t)] \\ -(1-\tau_I)\cdot P_{iI}(t)\cdot I_i(t) - (1-\tau_R)\cdot P_{iR}(t)\cdot R_i(t) \tag{3.2}$$

$$\dot{K}_i(t) = J_i(t) - \delta_K \cdot K_i(t) \tag{3.3}$$

$$I_i(t) = \varphi_i[J_i(t), K_i(t)] = J_i(t)\cdot\left[1 + \frac{\psi}{2}\cdot\frac{J_i(t)}{K_i(t)}\right] \tag{3.4}$$

$$\dot{H}_i(t) = \eta\cdot R_i(t)^{\alpha}\cdot H_i(t)^{\beta} + \frac{R_i(t)}{\sum_j R_j(t)}\left[\theta\cdot\sum_j R_j(t) - R_i(t)\right] - \delta_H\cdot H_i(t) \tag{3.5}$$

where the firm's objective is to optimally choose the inputs of labor X_{iL}, energy X_{iE}, material X_{iM}, physical investment I_i and R&D investment R_i to maximize an intertemporal profit stream V_i, subject to the technology constraints. In Eq. (3.1), V_i is formulated as a discounted present value of future profit streams from time t to an infinite future, with real interest rate r as discounting factor. In Eq. (3.2), current profit flow Π_i equals output revenues minus input costs, with $\tau_Q, \tau_C, \tau_I, \tau_R$ being corporate income tax, carbon tax on fossil energy inputs, investment tax credit and R&D tax credit, respectively.

Eq. (3.3) specifies the law of motion of physical capital stock K_i, its accumulation depends on fixed capital investment J_i and the rate of capital depreciation δ_K. Following the model of investment adjustment cost (e.g., Lucas, 1967; Treadway, 1969; Goulder and Schneider, 1999; McKibbin and Wilcoxen, 1999), Eq. (3.4) models the investment process that is subject to imperfect capital mobility and rising marginal costs of capital installation. That is, in order to install J_i unit of capital, a firm must buy a larger amount of investment goods I_i that depends on the rate of investment J_i/K_i and adjustment cost coefficient ψ.

Eq. (3.5) is the *innovation possibility frontier* (*IPF*) that describes the process of knowledge creation, where the accumulation of sector-specific knowledge stock $\dot{H}_i$ depends on R&D investment R_i, existing knowledge stock H_i, and intersectoral R&D spillovers $\left(R_i/\sum_j R_j\right)\cdot\left(\theta\cdot\sum_j R_j - R_i\right)$. The additive *IPF* specification implies that external R&D spillovers, corrected by local knowledge absorptive capacity, are perfect substitutes for in-house R&D.[8] η is knowledge creation efficiency. δ_H is the depreciation rate of knowledge obsolescence. The conditions $0<\eta<1$, $0<\alpha+\beta<1$ implies diminishing returns to R&D in innovation (Romer, 1990; Rivera-Batiz and Romer, 1991; Popp, 2004; Bosetti et al., 2008).

Note that, the specification of the *IPF* highlights the technology externality generated by inter-industry knowledge spillovers.[9] It postulates that each individual sector is exposed to

[8] In the specification of *IPF*, the addition between sector-specific R&D and intersectoral spillovers is based on the seminal work by Cohen and Levinthal (1989). For an alternative of multiplicative specification, see Bosetti et al. (2008).

[9] I draw on the intuitions from the seminal work of Schmookler (1966), Terleckyj (1974), Scherer (1982), and Griliches (1992). That is, due to the imperfect appropriability of knowledge, physical goods produced by individual sectors partially embody intangible knowledge created by its purposeful R&D investments. Other sectors, in the multi-sector economic transaction, can benefit from these external knowledge spillover through sectoral linkages along the supply chains – the

a public pool of intersectoral R&D and absorbs a fraction of this public good for building its in-house knowledge stock. In explicit, for any given sector i, the accessible R&D pool is created by the gap between sector-specific R&D and economy-wide one: $\theta \cdot \sum_j R_j - R_i$. θ denotes the technology externality resulting from intersectoral R&D spillovers, of which the value is determined by exogenous factors such as intellectual property protection system.[10]

Knowledge absorptive capacity is expressed as the ratio of sector-specific R&D relative to economy-wide one $R_i / \sum_j R_j$, suggesting that an individual sector's capacity of absorbing external knowledge depends on its indigenous R&D effort. Hence, specification in Eq. (3.5) suggests that indigenous R&D not only directly generates in-house know-how, but also enhance indigenous ability to absorb knowledge created elsewhere - the dual faces of R&D in knowledge creation (Nelson and Phelps 1966; Cohen and Levinthal, 1989; Keller, 1996).

Note that, the specification of *IPF* underlines three key factors in the process of knowledge creation: 1) purposeful R&D investment - the "no free lunch" assumption (to gain the economic benefits of innovation firms should commit to undertake own R&D efforts and not free ride on external knowledge spillovers); 2) current stock of knowledge - the "standing on the shoulders of predecessors" assumption (the more existing stocks of knowledge a sector has, the easier it is to create and apply new knowledge); 3) intersectoral R&D spillovers - the "pubic good sharing" assumption (any sector can benefit from the positive technology externality resulting from knowledge spillovers from other sector).

3.3 Model Implementation

To calibrate and implement the theoretical model in a numerical simulation, I construct a consistent benchmark dataset for model calibration. First, the year 2004 IO table of China is collected from the GTAP 7 Data Base (Narayanan and Walmsley, 2008).[11] Second, I adopt the GTAP data to our model structure by aggregating the 57 sectors into 12, and the 5 primary factor inputs into labor and physical capital. Finally, the 2004 IO table is scaled to

so-called intersectoral R&D spillovers (Clark et al., 2006, 2008).

[10] A value of one means that the benefits of research can fully spill over to a public R&D pool that is potentially available to all other sectors. A value of zero means that the benefits of research are exclusively appropriated by the sector undertaking research.

[11] The original GTAP data records intermediate production flows associated with 57-by-57 sectoss, 5 categories of primary factors (land, unskilled labor, skilled labor, capital and natural resources), and 4 components of final use (consumption, investment, government, and export).

approximate the Chinese economy in the year 2005 (the base year of simulation) using the 2005 growth rate of real GDP (9.1 percent).

These aforementioned steps produce a stylized IO table of China, which records the input flows of multiple commodities and primary factors into intermediate production and final use. However, as a departure from traditional calibration, this IO table is not well suited to calibrate a CGE model that features the R&D-induced TC, because it does not separately record the economic flows associated with R&D investment and knowledge inputs. To transform this stylized IO data, I need to undertake knowledge accounting to capture intangible knowledge flows. To this I now turn.

3.3.1 Knowledge Accounting

In the *System of National Accounts*, the stylized IO table treats corporate R&D expenditures as the current cost of production along with intermediate inputs, implying that only a portion of each intermediate transaction reflects the value of pure physical flows, with the remainder being the value of intangible knowledge flows embodied in that intermediate transaction flows (BEA, 2007; SNA, 2008).

In line with this principle, knowledge accounting can be conceptualized as follows: in a stylized IO table, the intangible knowledge flows matrix $\mathbf{\Omega}=[\omega_{ji}]_{j=1,\dots,n;i=1,\dots,n}$ is embodied in the intermediate transactions matrix $\mathbf{X}=[x_{ji}]_{j=1,\dots,n;i=1,\dots,n}$. The row sums of $\mathbf{\Omega}$ represent sector-specific R&D investment, $R_j=\sum_i \omega_{ji}$, and the column sums of $\mathbf{\Omega}$ denote the remuneration of knowledge capital as primary factor inputs into production, $H_i=\sum_j \omega_{ji}$. Based on the embodied technology hypothesis, the intangible knowledge flows embodied in the intermediate transaction can be estimated as: [12]

$$\underbrace{\frac{\omega_{j1}}{x_{j1}}=\dots=\frac{\omega_{ji}}{x_{ji}}=\dots=\frac{\omega_{jn}}{x_{jn}}}_{\text{Embodied technology hypothesis}}=\frac{\sum_i \omega_{ji}}{\sum_i x_{ji}}=\frac{R_j}{X_j} \Rightarrow \omega_{ji}=\frac{x_{ji}}{X_j}\cdot R_j \tag{3.6}$$

[12] *Embodied technology hypothesis* claims that intangible knowledge inputs must be embodied in specific tangible physical materials in order to manifest their economically useful characteristics. The knowledge accounting technique used in our work builds on the seminal work of Terleckyj (1974), Scherer (1982) and Griliches and Lichtenberg (1984), which used IO-based technology flow matrices to measure the intersectoral technology flows in an economic system.

where x_{ji} is the (j,i) cell of the intermediate transaction matrix $\mathbf{X}$ in the stylized IO table, representing the intersectoral transaction of intermediate inputs from sector j to i. ω_{ji} is the intangible knowledge flows embodied in that transaction. R_j, X_j denote R&D investment and intermediate production specific to sector j, respectively. The embodied technology hypothesis claims that, for any given commodity j, the knowledge embodiment ratio ω_{ji}/x_{ji} is invariant across sectors ($i = 1, 2, ..., n$) in intermediate production.

Given the available data of sector-specific R&D expenditure R_j and the product sales shares in intermediate transaction x_{ji}/X_j,[13] I use Eq. (3.6) to estimate intangible knowledge flows ω_{ji} embodied in the intermediate transaction x_{ji}, and hence capture all the entries in the knowledge flows matrix. Then, I vertically aggregate this knowledge flows matrix to create an additional row of knowledge inputs in the primary factors matrix $\mathbf{V}$, with each element being the value of knowledge input into production sector. Finally, the knowledge flows matrix is horizontally aggregated to generate an additional column of R&D investments in the final use matrix $\mathbf{G}$, with each element being the value of sector-specific R&D investment. This procedure hereby constructs a modified IO dataset with an explicit representation of R&D investments and knowledge inputs (see Fig. 3.1), based on which our CGE model with R&D-induced TC is calibrated.

3.3.2 Parameterization and Solver

The GEMPACK is used to solve the intertemporal optimization model.[14] The GEMPACK solver requires an initial equilibrium data as the benchmark point to calibrate the model. From this benchmark calibration point, the solver computes deviation of economic system to a new policy equilibrium as a response to a particular policy shock. For an intertemporal dynamic model, this benchmark equilibrium data is required to record the values of economic variables at each time point over the simulation periods, which is a time-series IO dataset (one for each time point) consistent with both intratemporal and intertemporal

[13] The sector-level R&D data are collected from the OECD ANBERD database. For our model sectoral mapping by reference to the OECD ANBERD sectoral classification, see Appendix 3.A. Product sale shares are calculated based on the intermediate transaction matrix in the available stylized IO table.

[14] GEMPACK is a suite of general-purpose CGE modeling software, which is more efficient than GAMS to solve an intertemporal optimization model (Codsi et al., 1992; Harrison and Pearson, 1996; Horridge and Pearson, 2011). For the GEMPACK codes of the model, see Appendix 3.C.

equations in the model.

To obtain such a full time-series dataset, we collect the available initial period (base year 2005) dataset and replicate it in future years over the period 2005-2030. Next, the Homotopy treatment is used to generate a non-steady-state baseline equilibrium dataset for model calibration.[15] Based on the consistent time-series benchmark dataset and model parameters (see Tab. 3.1), the theoretical model can be numerically simulated by the GEMPACK.

3.4 Results and Discussions

3.4.1 Alternative Scenario Settings

Recall that, I am motivated to examine the effectiveness of China's R&D investment and induced technology progress to curb its carbon emissions. To do that, I design and simulate two different scenarios, including: 1) Reference scenario: the innovative incentives are not factored into the decisions of private firms, with R&D investments and knowledge inputs are set to null in simulations. Without knowledge creation and TC, this scenario represents the baseline growth path; 2) R&D scenario: the mechanism of R&D-induced TC is incorporated into the producer problem, where R&D investment and knowledge creation are modeled as endogenous behaviors of profit-seeking firms. Its comparison with the reference scenario reflects the effect of R&D-induced TC. In Sections 3.4.3-3.4.4, I will consider additional policy scenarios (innovation and climate policies) and their impacts on reducing carbon emissions.

[15] Normally, the initial period is not in a steady-state (SS) equilibrium, the dataset created by replicating initial period data into future periods thus can't be used as a baseline to calibrate intertemporal equations (e.g., Eq., (3.3), Eq. (3.5)). To remedy this problem, we add a Homotopy term into each intertemporal equation and carry out a simulation where the Homotopy variables are shocked. This simulation then generates a non-SS time-series dataset that can be used a baseline to calibrate both intra- and inter-temporal equations in our model. The Homotopy treatment is automated by the TABLO program in GEMPACK. For the details, see Codsi et al. (1992), and Wendner (1999).

Table 3.1: Substitution elasticity and other parameters values

	σ^Q	σ^Z	σ^E	σ^M	σ^A	σ^T
Production sectors						
Electric utility	1.0	0.8	0.2	1.0	2.8	1.0
Gas utilities	1.0	0.8	0.9	0.2	2.8	1.0
Petro refining	1.0	0.5	0.2	0.2	2.1	1.0
Coal mining	1.0	1.7	0.2	0.5	3.0	1.0
Crude oil & gas	1.0	0.5	0.1	0.2	5.0	1.0
Agriculture	1.0	1.0	1.1	2.8	0.9	1.0
Forestry	1.0	1.3	0.6	1.7	2.5	1.0
Mineral mining	1.0	0.9	0.9	0.2	2.5	1.0
Durable	1.0	0.4	0.8	0.2	3.0	1.0
Non-durable	1.0	1.0	1.0	0.1	3.0	1.0
Transportation	1.0	0.5	0.2	0.2	1.9	1.0
Services	1.0	0.3	0.3	3.0	1.9	1.0
τ_Q	Corporate short-run profit tax rate					0.1
τ_I	Investment tax credit					0
τ_R	R&D tax credit					0
τ_C	Carbon tax imposed on fossil fuel input					0
α	Elasticity of knowledge creation to R&D investment					0.2
β	Elasticity of knowledge creation to existing knowledge stock					0.55
η	Sector-wide efficiency of knowledge creation					1
r	Real interest rate					0.05
δ_K	Depreciation rate of physical capital					0.05
δ_H	Depreciation rate of knowledge capital					0.1
ψ	Investment adjustment cost coefficient					4
θ	Externality of intersectoral R&D spillovers					1

σ^Q: Elasticity of substitution between knowledge and physical input composite

σ^Z: Elasticity of substitution among capital, labor, energy, material (KLEM) physical inputs.

σ^E: Elasticity of substitution among intermediate energy goods.

σ^M: Elasticity of substitution among intermediate material goods.

σ^A: Armington elasticity of substitution between domestic and imported goods varieties.

σ^T: Elasticity of output transformation between domestic and exported goods varieties.

Note: For the substitution elasticity, twelve production sectors have sector-differentiated parameter values. For other parameters, the twelve production sectors are assumed to have the same parameter values in baseline simulation.

Source: McKibbin and Wilcoxen (1999); Goulder and Schneider (1999); Popp (2004); Sue Wing (2006); Bosetti et al. (2008); Wang et al. (2009); Narayanan and Walmsley (2008); Otto et al. (2008).

3.4.2 Impacts of R&D-induced TC

For insights into the effect of R&D-induced TC, I simulate economic and emission growth paths under the two aforementioned scenarios. As Fig. 3.3(a) shows, GDP in the reference scenario is projected to grow by 6.3% annually from $2327 to $9650 billion dollars between 2005 and 2030. In contrast, GDP in the R&D scenario rises by 5 folds from $2327 to $11182 billion dollars during the same period, with an annual average growth rate of 7.6%.[16] This suggests a stronger growth with the stimulus of R&D investment and induced innovation.

Climate repercussions resulting from the R&D-induced TC are shown in Fig. 3.3(b). The reference scenario exhibits a rising trajectory of carbon emissions that grow by 4.2% annually from 5100 to 13800 Mt. In comparison, carbon emissions in the R&D scenario are set to rise from 5100 to 12300 Mt between 2005-2030 - an average annual growth rate of 3.5%. In terms of percentage change, R&D-induced TC is seen to drive China's absolute emissions below its projected baseline levels by 8.5% in 2020 and 11.2% in 2030. As a result, cumulative emission cuts relative to the reference level are estimated to reach 22 gigatons over the period 2005-2030, indicating that technological innovation has a notable effect to curb the baseline (no-innovation) emission levels. It is also shown that the reference scenario projects a path where China's carbon intensity is likely to fall from its 2005 level of 2.2 to a 2030 level of 1.4 tons per thousand dollars.[17] In contrast, that intensity in the R&D scenario will be cut deeper to 1.1 tons per thousand dollars at the end of the simulation.

Furthermore, the multi-sector CGE framework is employed to investigate the effect of R&D-induced TC on emission abatement potential at the sector level. This is done by examining the sector-specific cumulative emission cuts relative to the reference levels. As Fig. 3.4(a) shows, the sectors of durable manufacturing, electricity and transport accommodate higher abatement potential from innovation. This is because current production recipes of these sectors rely on intensive inputs of fossil fuels. Once R&D investment is undertaken for knowledge creation, production technologies in these sectors have a large room of applying knowledge to substitute for physical inputs. For example, R&D in the electric utility sector can foster development of low-carbon energy technology like wind and solar and produce "green" electric power, satisfying electricity demand without increasing carbon emissions.

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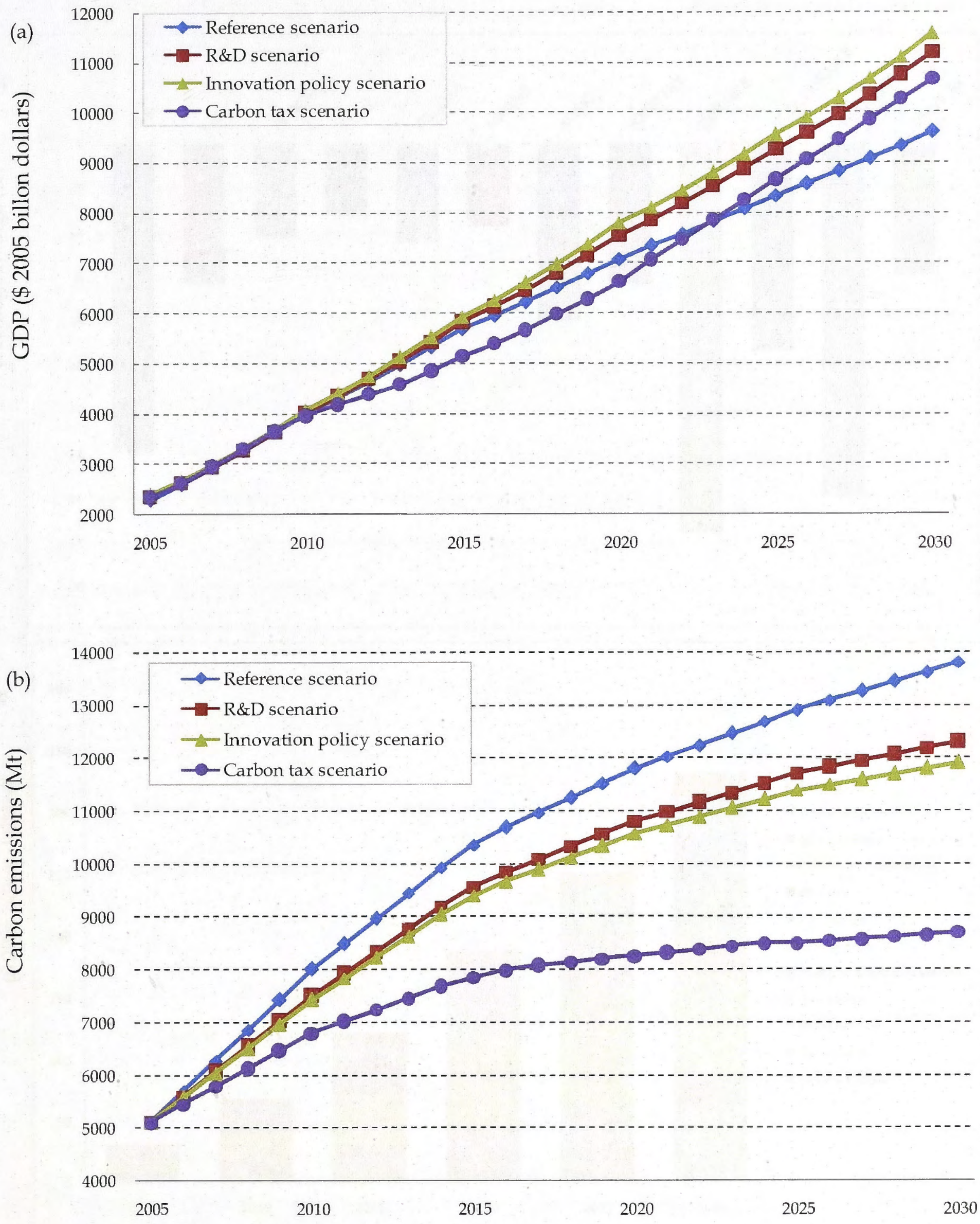
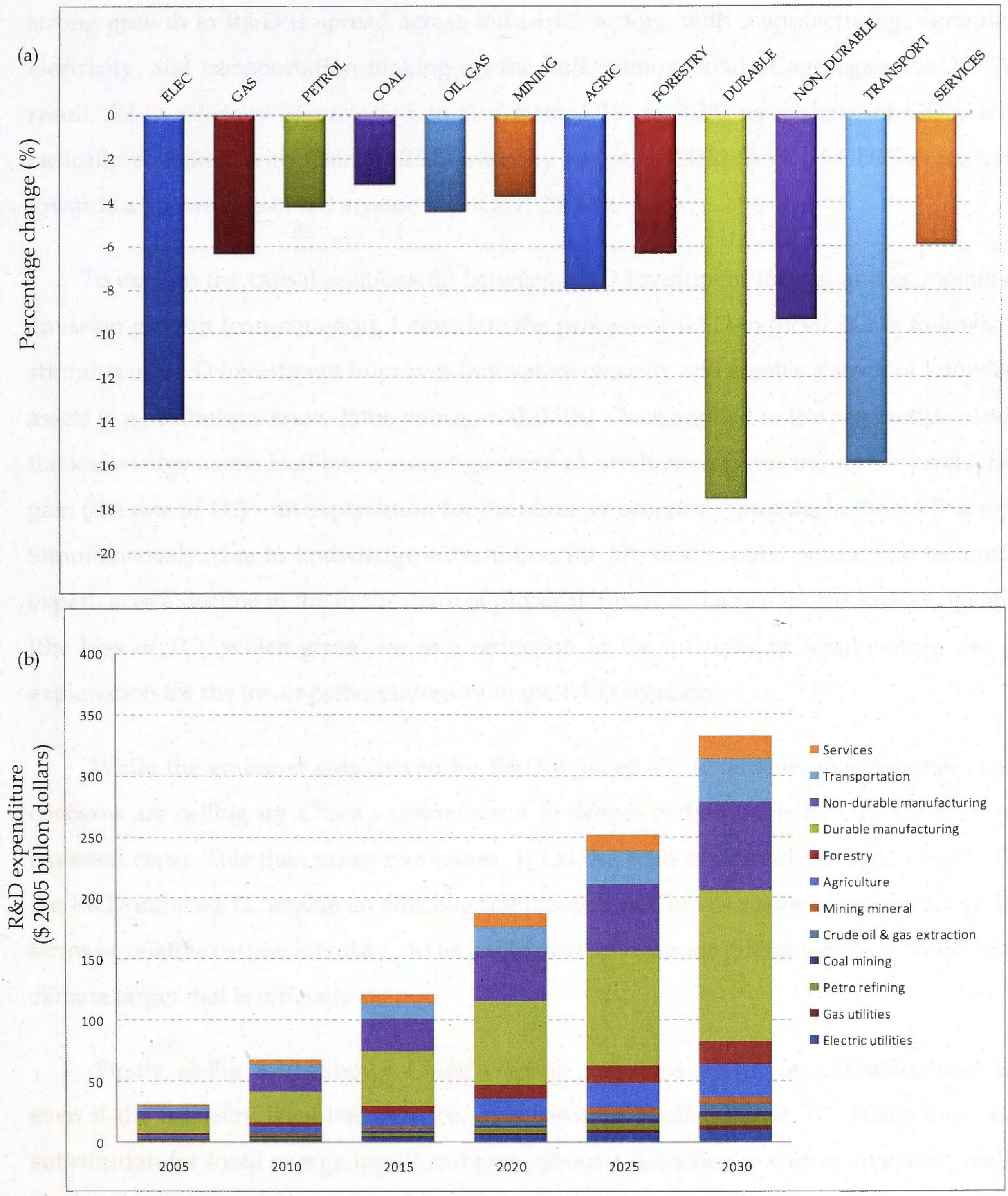
[16] All measurements of output values are real GDP (constant price estimate) in unit of 2005 U.S. dollars (year 2005 is the base period). Differences in real GDP reflect changes in output volume.
[17] China is normally using carbon intensity targets to bind its climate responsibility.

Figure 3.3: China's GDP and carbon emissions growth paths



Note: (a) China's GDP growth paths under four scenarios (reference, R&D-induced TC, innovation policy, carbon tax); (b) China's CO_2 emissions growth paths under four scenarios (reference, R&D-induced TC, innovation policy, carbon tax).

Figure 3.4: Intertemporal profiles of R&D investment and its effect to lower carbon emissions



Note: (a) Effect of R&D-induced TC on sector-level cumulative emission cuts relative to the reference (no R&D-induced) emissions levels; (b) Intertemporal profiles of economy-wide R&D investments and its sectoral composition.

As one of the driving forces of the aforementioned changes, the changing trend of R&D investment is shown in Fig. 3.4(b). Between 2005 and 2030, the economy-wide R&D investments are expected to grow by 12% annually from $31 to $335 billion dollars. The strong growth in R&D is spread across industrial sectors, with manufacturing, agriculture, electricity, and transportation making up the bulk (almost 80%) of aggregate R&D.[18] As a result, R&D intensity is projected to rise from 1.3% to 3.2% as a share of GDP, which basically coincides with China's R&D intensity target by 2020 (2.5% of GDP) in its transit towards a knowledge-based economy (MOST, 2006b).

To explain the causal relationship between R&D investment (cause) and economic and emission growth (consequence), I elucidate the process of R&D-induced TC as follows. The stimulus of R&D investment improves innovative capacity and creates a stock of knowledge assets (e.g., technique know-how, managerial skills). Once applied to the production process, the knowledge assets facilitate a reconfiguration of production factor inputs for productivity gain (the rate of TC) – an explanation for the stronger economic growths in the R&D scenario. Simultaneously, due to knowledge substitution for physical inputs, production technology experiences a decline in the input share of physical inputs and a rise for the knowledge input (the bias of TC), which gives rise to a reduction in the intensity of fossil energy use - an explanation for the lower carbon intensity in the R&D scenario.

While the emission cuts driven by R&D-induced TC is notable, international climate concerns are calling for China's commitment to deeper carbon intensity cuts (or even hard emission caps). This then raises two issues: 1) On the basis of absolute emission levels, does the R&D-induced TC enable an effective stabilization of China's rising emission trends; 2) In terms of relative carbon intensity, do technological innovations guarantee the achievement of climate target that is officially set out.

Firstly, as Fig. 3.3(b) shows, China's carbon emissions are still on a climbing trajectory, even if the intensity level has been cut as a result of R&D-induced TC. While knowledge substitution for fossil energy inputs can bring about a reduction in carbon intensity, fuelling China's rapidly expanding economy still entails mammoth uses of physical factor inputs.

[18] The reason is that, R&D investments in these sectors have a higher level of marginal benefit due to higher innovation efficiency and marginal products of knowledge input. Given a certain level of marginal cost of R&D (the purchase price of raw R&D goods), producers in these sectors would hence rationalize their economic behavior by undertaking more R&D investments.

This unsurprisingly leads to a continuous increase in the absolute levels of fossil energy uses and carbon emissions, without a significant effect to stabilize the emission growth trend.[19] Secondly, at the 2009 Copenhagen climate summit, China unilaterally pledged to cut its carbon intensity by 40-45% below its 2005 levels by 2020, and this target is likely to aim for a 60-65% carbon intensity cut by 2030 relative to its 2005 levels. However, simulation results show that the R&D-induced TC will only drive down China's 2005 carbon intensity level by about 35% by 2020 and 50% by 2030, which is well below the pledged target. Moreover, if the uncertain nature of innovation is taken into account, massive R&D investment can't fully translate into new knowledge creation and application in production to substitute for fossil energy inputs, China's carbon intensity level will still remain high and fail to fulfill the climate target.[20] In this regard, there is a growing need for China to call for additional efforts on top of the existing private R&D investment in order to meet the pledged climate target.

In this context, China's technology strategy is likely to be far from sufficient to realize climate-friendly "green" innovations. The main reasons are as follows. From the perspective of microeconomic foundation, R&D investment is an innovative incentive of private firms to pursue economic profitability. If the externality costs caused by environmental damages are not fully internalized, the individual micro-level firms have no incentive to reduce fossil fuel uses and carbon emission in the pursuit of profitability. As a result, China's innovation pattern tends to focus on pushing domestic industries upstream in global value chains through developing competitive general-purpose technologies, without the motivation to capture the small niche market of low-carbon energy supply technologies. Obviously, this innovation pattern is "normal" with carbon neutrality, rather than a carbon-saving "green" innovation (Nordhaus, 2011).[21]

[19] This may reflect the reason why Beijing has repeatedly rejected the calls to commit to an emission peak year. China's fast expanding economy will consistently reinforce the increases in its emissions (IEA, 2007).

[20] For a detailed discussion about the uncertainty in climate policy design, see McKibbin and Wilcoxen (2009).

[21] While China is now gaining speed as a world leader in the production of renewable energy technology, the bulk of these capacities are used for exports instead of domestic deployment. A inhibiting factor is the problem of grid integration of renewable energy (e.g. Kahrl et al., 2011; de la Tour et al., 2011). Basically, China maintains its focus on key research areas and enabling general-purpose technologies like biotechnology, nanotechnology, pharmaceuticals, large-scale IC manufacturing, telecommunication, large aircraft and aerospace projects (MOST, 2006b).

3.4.3 Innovation Policy Scenario

The results in Section 3.4.2 reveal that, while China is becoming increasingly committed to R&D, the nation still confronts a gap between achieving emissions cuts and expected climate targets. To bridge this gap, complementary policies are needed to create additional emission reductions. In this section, I examine the effect of innovation policies including public R&D subsidies and intellectual property right (IPR) protection. Climate policy (e.g., carbon tax) will be examined in the next section.

Recall that, in the R&D scenario the R&D investment spending is fully financed by output sales revenues of the private firms, but broader R&D investments can be stimulated if public R&D support is in place, where the government can use tax revenues to subsidize private R&D and hence encourage more innovative activities.[22] Moreover, public R&D subsidy should be biased towards innovation in the non-fossil fuel sectors (electricity and seven non-energy sectors), so that their reliances on fossil fuel inputs can be reduced. To represent this type of innovation policy, I impose a policy shock of raising the R&D subsidy rate $\tau_R = 0.3$ in all non-fossil fuel sectors, which means 30% of R&D spending is financed by government fiscal revenues (OECD, 2008).

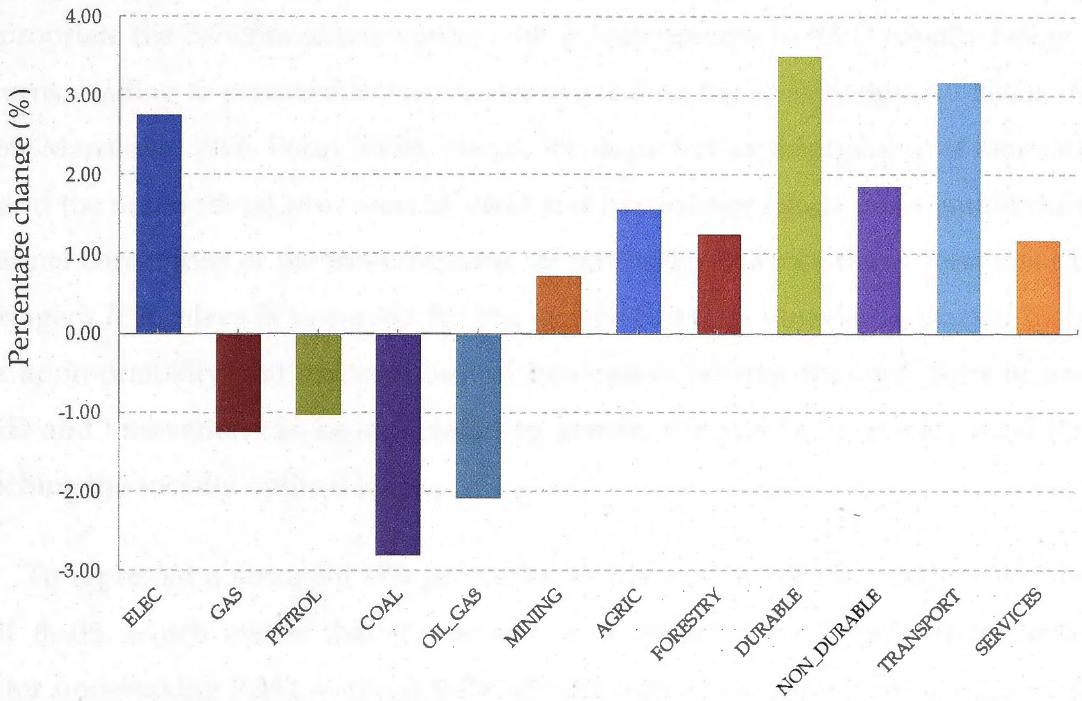
Simulation results show that, in the presence of public R&D subsidy, private firms have stronger innovative incentives, where R&D investment will continue to rise to 385 billion dollars in 2030 - a level that is 14% higher than that without that subsidy. As a result, GDP is projected to grow by 7.7% annually from $2327 to $11381 billion dollars between 2005-2030 (see Fig. 3.3), which features a stronger economic growth path than that in the R&D scenario. Meanwhile, carbon emissions are likely to rise from 5100 to 12019 Mt, with a growth rate of 3.4% that is slightly lower than the rate in the R&D scenario (3.5%). This is due to more knowledge available to substitute for fossil energy uses in the production process.

In addition to the economy-wide effects, I further examine the effect of the biased R&D subsidy on cumulative output changes at the sectoral level. As Fig. 3.5 shows, fossil fuel sectors are likely to suffer from output losses under the innovation policy intervention, while

[22] From government budget constraint, it is clear to observe that in equilibrium the government will target part of the existing tax revenues (e.g., corporate profit tax, household income tax) as well as additional tax revenues (e.g., carbon tax in the climate policy scenario), so that the public R&D subsidies to support private innovation can be financed.

outputs in other sectors will continue to grow. The reasons are twofold. Firstly, with public R&D subsidies biased towards the non-fossil fuel sectors, the expansion of R&D resources in these sectors will reduce (crowd out) that is available to fossil fuel sectors due to the supply

Figure 3.5: Effect of biased R&D subsidy on cumulative outputchanges at the sectoral level



Note: Public R&D subsidy is set to be biased towards innovation in eight non-fossil fuel sectors, so that their reliances on fossil fuel inputs can be reduced. The effect is measured as the percentage changes of cumulative output levels driven by the R&D subsidy policy shock relative to the output levels without that subsidy.

constraint of R&D goods.[23] Knowledge creation and production TC are hereby inhibited in fossil fuel sectors, generating the crowing-out effect in the R&D pool. Secondly, the biased R&D subsidies serve to encourage non-fossil fuel sectors to innovate and apply knowledge in production, which substitutes for the use of fossil fuels. As a result, the declining demand will automatically drive down the output supply of fossil fuel sectors in order to clear the market, which represents the opportunity cost of this biased R&D subsidy. However, the productivity growth in non-fossil fuel sectors under the biased R&D supports can partially

[23] On the general issue of crowding out of R&D, see Hall and van Reenen (2000), Hall (2002a,b), David and Hall (2000), David et al. (2000).

offset the output declines in fossil fuel sectors, without a potential loss of aggregate outputs. Put another way, the R&D subsidies biased towards non-fossil fuel sectors, by restricting innovation and TC in fossil fuel sectors, can diminish the contribution of fossil fuel industries to aggregate production outputs, which may be one of the appealing technology strategies to restructure a carbon-intensive economy into a low-carbon one.

Now turn to the other type of innovation policy: IPR protection. In principle, due to the positive technology externality resulting from knowledge spillovers, innovators can't fully appropriate the benefits of innovation with private returns to R&D usually below the social returns, leading to private R&D investments less than the socially optimal levels (Nordhaus, 1969; Mansfield, 1996; Popp, 2006). Hence, the imperfect appropriability of innovations gives rise to the sub-optimal provision of R&D and knowledge goods in an equilibrium without external corrections of the imperfections. Accordingly, The role that government regulation (stringent IPR) plays is to correct for the imperfections in innovation market by improving the appropriability and excludability of innovation, so that the incentives of undertaking R&D and innovation can be stimulated by private firms, making private R&D investments reaching the socially optimal levels.

To represent a stringent IPR protection in the model, I scale down the values of θ by half θ=0.5, which means that the benefits of innovation are largely appropriated by the sector undertaking R&D, without fully spilling over to the public knowledge pool (a lower level of intersectoral knowledge spillover). Simulation results show that, the stringent IPR protection strengthens R&D investment and innovation, which pushes the growth of GDP to 11509 billion dollars by 2030 - an additional 1.1% increase on top of the GDP levels achieved by public R&D subsidies. Carbon emissions are likely to drop further to 11892 Mt by 2030 – an additional 0.8% reductions relative to the emission levels under public R&D subsidies. The reason for this improvement is that, IPR protection serves to eliminate intersectoral knowledge spillovers in the imperfect innovation market, so that the benefits of R&D and knowledge creation are largely appropriated by the innovating sector, with a lower level of R&D spillover into public knowledge pool. Accordingly, to gain the benefits of innovation, private firms need to undertake more purposeful R&D, without the incentive of free riding on external R&D spillovers. Given that more R&D efforts are taken by individual sectors, the accumulated knowledge is more likely to substitute for fossil fuel in production and hence further lower carbon emissions.

In summary, innovation policies including public R&D subsidies and IPR protection enable a further reduction in China's carbon intensity, but the effect is relatively minor, with only 1-2% additional cuts on top of the intensity level achieved in the R&D scenario. Consequently, the joint effect of private R&D efforts and public R&D supports is to cut China's carbon intensity by 38% by 2020 (1.36 tons per thousand dollars) and 53% by 2030 (1.03 tons per thousand dollars) relative to its 2005 levels, which still fall short of the pledged climate target (40-45% cuts by 2020, 60-65% cuts by 2030). The ineffectiveness of innovation policies as the sole strategy of carbon abatement is primarily due to the diminishing return to R&D investment in innovation.[24] At the same time, stringent IPR system serves to protect innovation excludability *ex post*, which is ancillary to the *ex ante* incentive of R&D investment, that is, the inventive response of profit-seeking firms to input price changes.

3.4.4 Climate Policy Scenario

As argued previously, the emission cuts achieved by R&D investment and innovation may fall short of the pledged climate target. To bridge this gap, an emission-based direct climate regulation (e.g., carbon tax) should be thought of as necessary. On the one hand, as the transition to a hard cap on long-run absolute emission levels,[25] carbon taxation provides a market-based solution to help handle the challenge faced by China's current administrative measures on emission abatement.[26] On the other hand, as private agents have the *ex ante* innovative response to input price change, a carbon price signal can induce private firms to undertake carbon-saving innovation.

I thus introduce a carbon tax of $20 dollars per ton of carbon dioxide from 2012, rising at

[24] Worries also exist at the central leadership level about whether massive public R&D can bear productive and sustainable innovations. Reportedly, many Chinese R&D activities have been plagued by research fund waste, haste and shoddy workmanship, and low quality standards. A political culture of corruption, prestige projects and top-down obedience could hinder the efficient use of public R&D funds (e.g., Shi and Rao, 2010).

[25] China's share of historical cumulative emissions between 1900-2030 is expected to rise to 16%, approaching that of the U.S. (25%) and the E.U. (18%). China's per capita emission in 2030 is projected to approach that of OECD Europe. Provided that developed countries have make concrete efforts of absolute emissions cuts, China will lost its ground not to take on hard emission caps, even if it remains on a climbing trajectory (IEA, 2010).

[26] This is reflected by China's difficulty in achieving its energy saving target during the 11th five year cycle. Local governments conducted forceful administrative measures, such as power plant shutdown, electricity and vehicle use control. As abatement levels become more stringent, such measures will become costly to achieve climate targets (Zhang, 2011).

a rate of 5% to $50 dollars per ton by 2030.[27] As Fig. 3.3(b) shows, the carbon tax generates a notable effect to stabilize the emission growth path, pushing down the emission levels by 25% to 8702 Mt by 2030. As a result, carbon intensity falls by 47% in 2020 and by 65% in 2030 relative to the 2005 levels, reaching a level of 0.78 tons per thousand dollars at the end of time frame. Put differently, on top of private R&D investment and public innovation policies, climate policy creates additional carbon intensity cuts of 9% in 2020 and 12% in 2030. This translates into additional absolute emissions cuts of 21% in 2020 and 28% in 2030. Over the period 2005-2030, carbon tax reduces the cumulative emission levels by about 22%, of which the sectoral composition is shown in Fig. 3.6(a). Coal sectors have the highest level of cumulative emissions cuts (50-60%), followed by oil, natural gas and electric sectors (20-30%), with a modest level of cumulative abatement (10-20%) occurring in non-energy sectors.

It comes as no surprise that the environmental benefit of deeper emission cuts achieved by carbon taxation is at the cost of production output losses. As Fig. 3.3(a) reveals, putting a carbon price on the economy incurs a growth slowdown in the near term (2012-2020). After that, the economy will absorb the price shock and continue its normal growth path without compromising long-run economic prospect. This simulation result basically coincides with other climate policy modeling studies (e.g., McKibbin, 2008; McKibbin and Wilcoxen, 2004, 2009). In explicit, GDP is likely to grow by 6.8% annually to $11153 billion dollars in 2030. Over the period 2005-2030, the present-value cumulative GDP losses reach a level of $2981 billion dollars (2.1% GDP losses), of which the sectoral composition is displayed in Fig. 3.6(b). Non-energy sectors have cumulative output losses of less than 5%, and the carbon-intensive fossil fuel sectors suffer precipitous output declines of roughly 15-25%.

We also look at the impact on prices. It is simulated that, as carbon tax raises the costs of using fossil energy that is a component in household consumption bundle, the Consumer Price Index (CPI) will slightly rise by 0.5% in the short run (2010) and reach the highest level (by 1.2%) by 2015, when the policy shock of carbon tax is imposed by 2012. After the peak year 2015, CPI will increase by a moderate range of 0.6-0.8% in the long run (2020-2030). In terms of changes in relative prices of energy goods as compared to others, we look at the price ratio of energy relative to non-energy (material) goods bundle. It is simulated that this

[27] The timing and level of carbon tax are set according to the shadow carbon prices calculated by IEA (2010), which represents a hypothetical policy experiment. With regard to the recycling of carbon tax revenues, I assume that the revenues collected from carbon taxation directly flow into the government revenues side, and are used to balance government's budget constraint.

price ratio will increase by 5% in the short run and reach a peak level of about 11% around the year 2015, when the carbon taxation immediately drives the price divergence between energy and non-energy goods. However, changes in this price ratio will return to a lower range of about 4-7% between 2020-2030, suggesting a price convergence between energy and non-energy goods in the long run. That's because in a multi-sector general equilibrium with intersectoral linkages, energy goods (as intermediate production inputs) are intensively used in non-energy sectors for producing non-energy goods, particularly for an energy-intensive economy like China. Accordingly, in the presence of intersectoral linkages, price changes in energy goods can eventually pass through into productions in non-energy goods sectors, making non-energy goods prices moving in the same direction with energy goods prices.

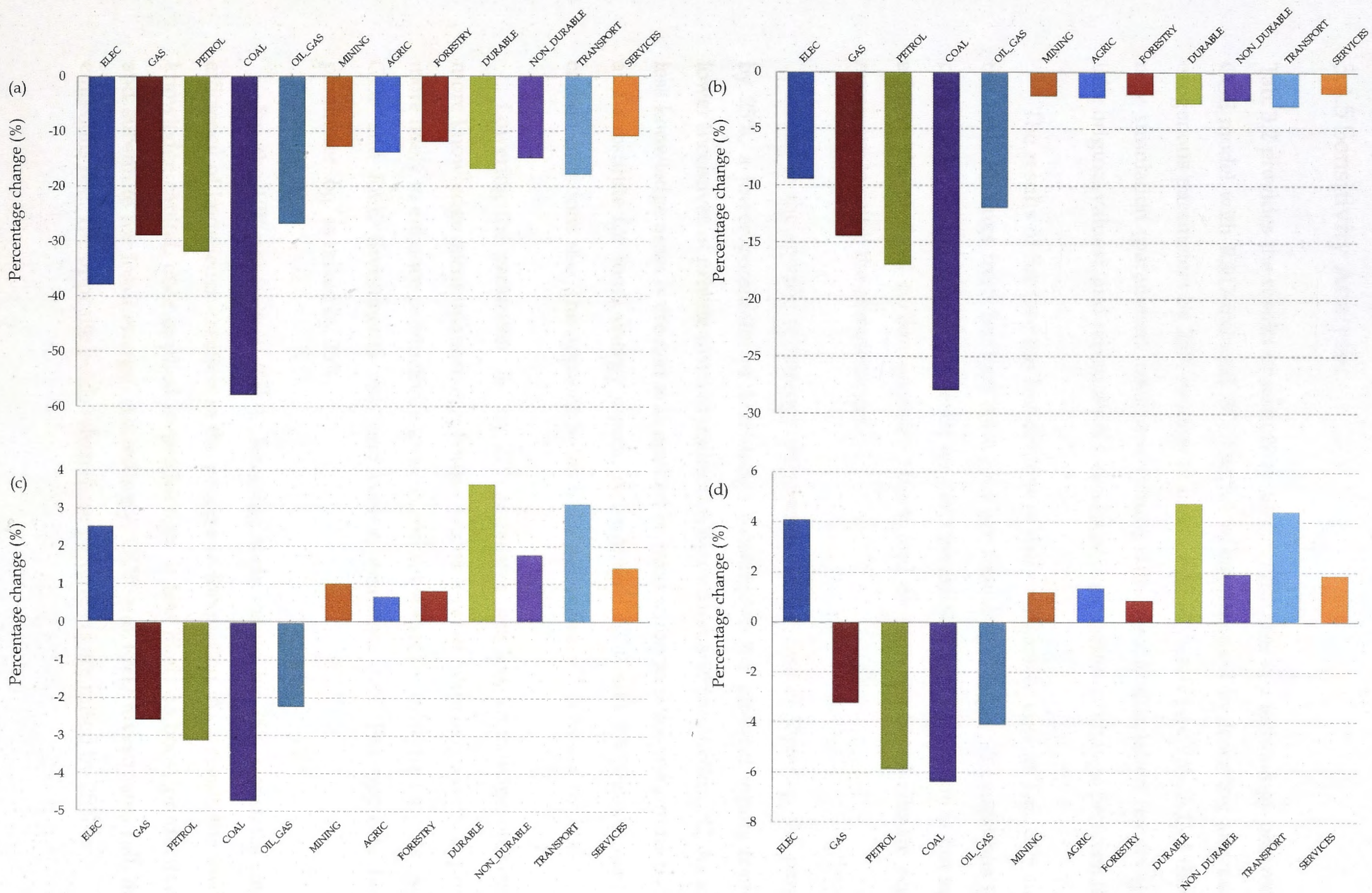
In addition to the economic costs (output losses) and environmental benefits (carbon savings), stringent climate regulation can create the other benefit: innovation inducement. Provided that private firms tend to advance production techniques as their inventive response to input price changes, putting a price on carbon-intensive fossil fuels can induce private firms to create and apply knowledge in production, so that the higher cost burden can be avoided. This phenomenon is demonstrated in Fig. 3.6(c), although reductions in production output incurred by carbon tax would diminish output sales revenues and hence the absolute levels of R&D spending, R&D intensity (R&D-output ratio) does not necessarily drop across sectors. The decline in cumulative R&D spending exceeds the loss in cumulative output in fossil fuel sectors, but falls short of those in other sectors. Consequently, the R&D intensity rises slightly across a range of less carbon-intensive industries like manufacturing, transport, and electric utilities, indicating that innovation is induced by carbon taxation in these sectors.

Changes in knowledge-output ratio (the input share of knowledge in production) also appear to coincide with the phenomenon of innovation inducement. As Fig. 3.6 (d) shows, knowledge-output ratio falls sharply in fossil fuel sectors but rise slightly in non-fossil fuel sectors, suggesting that knowledge are reallocated from fossil fuel sectors to non-fossil fuel sectors that accommodate the higher potential of knowledge substitution for fossil fuel inputs. This finding is basically consistent with the *induced innovation hypothesis*: changes in the relative prices of production input are in itself a spur to a technological alternative that lowers the use of that relatively expensive factor (Hicks, 1932).[28]

In summary, emission-based climate regulation through carbon taxation can generate one cost (production output losses) and two benefits (carbon saving, innovation inducement). In particular, the inducement of innovation and TC can partially mitigate the deadweight losses incurred by tax distortion, making possible the process of transition into a low-carbon economic growth pattern.

[28] For theoretical expositions of the induced innovation hypothesis, see Kennedy (1964), Kamien and Schwartz (1968), Goulder and Schneider (1999) and Sue Wing (2006). For empirical evidences, see Newell et al. (1999) and Popp (2002).

Figure 3.6: Effect of carbon taxation on environmental benefits, economic costs, and innovation inducement



Note: (a) Effect of carbon tax on sector-level cumulative emission cuts; (b) Effect of carbon tax on sector-level cumulative production output losses; (c) Effect of carbon tax on sector-level R&D intensity (R&D-output ratio); (d) Effect of carbon tax on sector-level knowledge-output ratio (input share of knowledge in production).

3.4.5 Sensitivity Analysis

Tab. 3.2 provides the results of sensitivity analysis (SA) for key technology parameters in the CGE model with R&D-induced TC. The SA is implemented by lowering and raising these exogenous parameters by 25% relative to their original values (see Tab. 3.1). I then compare new simulation (parameters take new values) with regular simulation results (parameters take original values), and report the SA results as the percentage change between them.

The results of SA (see the last column of carbon intensity cuts in Tab. 3.2) suggest that the basic findings from Sections 3.4.1-3.4.4 are robust to changes in exogenous technology parameters. That is, sole dependence on R&D investment and innovation is not sufficient to achieve the pledged carbon intensity target, and an emission-based climate regulation is necessary to fulfill the climate target.

Turn to the specific technology parameters, in the case of lowering the parameter σ^Q by 25%, a lower possibility of knowledge substitution for physical inputs translates into lower incentives of private firms to undertake innovation and production TC. As a result, the less knowledge asset is created and applied in production to stimulate productivity growth and substitute for fossil energy inputs. Accordingly, GDP and R&D investment falls, and carbon emissions rise. The opposite holds if the parameter σ^Q is raised by 25%.

Lowering the parameter δ_H by 25% translates into less knowledge obsolescence and more knowledge accumulation. Applying a higher level of knowledge stock in production is more likely to enhance productivity growth and substitute for fossil fuel inputs. Accordingly, GDP and R&D investments rise, and carbon emissions fall. The opposite holds if the parameter δ_H is raised by 25%.

For the *IPF* parameters α,β,η, lowering their values by 25% translates into a lower efficiency of knowledge creation in the process of innovation. As a result, the lower level of knowledge capital, once applied in production, is less likely to boost productivity growth and substitute for fossil energy. Accordingly, GDP and R&D investments fall, and carbon emissions rise. The opposite holds when these parameters are raised by 25%.

Table 3.2: Results of sensitivity analysis

		GDP [a]			Carbon Emissions [b]			R&D Investment [c]			Carbon Intensity Cuts [d]		
	Scenario [e]	1	2	3	1	2	3	1	2	3	1	2	3
σ^Q	Low [f]	-0.72%	-0.53%	-1.31%	1.94%	1.62%	2.51%	-3.48%	-3.15%	-4.51%	45.6%	48.2%	60.8%
	High	0.54%	0.27%	1.75%	-1.73%	-1.27%	-2.65%	3.81%	3.52%	4.76%	54.7%	57.5%	68.5%
δ_H	Low	0.43%	0.32%	0.79%	-1.16%	-0.97%	-1.51%	2.09%	1.89%	2.71%	52.1%	55.3%	67.3%
	High	-0.32%	-0.16%	-1.05%	1.04%	0.76%	1.59%	-2.29%	-2.11%	-2.86%	47.2%	50.8%	62.8%
α	Low	-0.29%	-0.21%	-0.52%	0.78%	0.65%	1.00%	-1.39%	-1.26%	-1.80%	48.5%	52.2%	63.7%
	High	0.22%	0.11%	0.70%	-0.69%	-0.51%	-1.06%	1.52%	1.41%	1.90%	50.9%	53.9%	65.2%
β	Low	-0.36%	-0.27%	-0.66%	0.97%	0.81%	1.26%	-1.74%	-1.58%	-2.26%	47.2%	51.5%	62.8%
	High	0.27%	0.14%	0.88%	-0.87%	-0.64%	-1.33%	1.91%	1.76%	2.38%	51.7%	54.2%	66.5%
η	Low	-0.50%	-0.37%	-0.92%	1.36%	1.13%	1.76%	-2.44%	-2.21%	-3.16%	46.9%	49.6%	62.7%
	High	0.38%	0.19%	1.23%	-1.21%	-0.89%	-1.86%	2.67%	2.46%	3.33%	52.6%	55.2%	67.7%

[a] Percentage change of cumulative GDP in new simulation relative to that in regular simulation.
[b] Percentage change of cumulative carbon emissions in new simulation relative to that in regular simulation.
[c] Percentage change of cumulative R&D investment in new simulation relative to that in regular simulation.
[d] Year 2030 carbon intensity cuts relative to the year 2005 carbon intensity level.
[e] Scenario 1,2,3 refer to R&D-induced TC scenario, innovation policy scenario, and carbon tax scenario, respectively.
[f] Low and High refer to lowering and raising exogenous parameters by 25% relative to their central case values, respectively.

σ^Q: Elasticity of substitution between knowledge and physical input
δ_H : Depreciation rate of knowledge capital
α : Elasticity of knowledge creation to R&D investment
β : Elasticity of knowledge creation to existing knowledge stock
η : Efficiency of knowledge creation

3.5 Concluding Remarks

This chapter incorporates the mechanism of R&D-induced TC into a CGE model to represent the endogenous process of technological innovation, which is used to quantitatively examine the effectiveness of China's indigenous R&D and innovation to curb its carbon emissions. The results provide various implications for China's strategy to address climate mitigation: 1) Technological progress induced by R&D commitment has a notable effect to curb China's carbon emissions levels, with the sectors of manufacturing, electricity, and transport having the highest carbon abatement potential from innovation; 2) Indigenous R&D investments are important as the technology strategies to address climate change mitigation, but the sole dependence on R&D is far from sufficient to achieve the pledged climate target, because China's innovation pattern is basically "normal" with a focus on productivity improvement rather than carbon saving; 3 Innovation policies (public R&D subsidy and stringent IPR) can strengthen R&D investment and further reduce carbon emissions, but this complementary effect is still minor and insufficient to meet the stipulated climate target; 4) Emission-based climate regulation through carbon taxation are necessary to fulfill the emission reduction target, but achieving this carbon-saving benefit is at the cost of sizable production output losses; 5) Stringent climate regulations induce the incentive of private firms to innovate and technical upgrading, which can partially mitigate the deadweight losses incurred by carbon tax distortion.

Needless to say, a number of model extensions are needed in future works. In particular, the current modeling framework only focuses on indigenous innovation within the single economy, putting aside the potential foreign knowledge diffusion. As China is increasingly integrated into the globalized world economy through trade, FDI, human capital mobility, and research cooperation, foreign knowledge diffusion may become increasingly important to complement indigenous R&D in innovation. It is thus needed in future studies to examine the mechanism of international technology diffusion and its effect on low-carbon innovation and climate change mitigation.

Appendix to Chapter 3

3.A Model sectoral classification and mapping by reference to the GTAP and OECD ANBERD

Sector number/name in our mode	GTAP sector numbers	OECD ANBERD sector number
1. Electric utilities	43	40
2. Gas utilities	44	41
3. Petroleum refining	32	23
4. Coal mining	15	10
5. Crude oil & gas extraction	16-17	11
6. Mineral mining	18	12-14
7. Agriculture	01-12, 14	01, 03-05
8. Forestry & wood products	13, 30	02, 20
9. Durable manufacturing	34-42	26-37
10. Nondurable manufacturing	19-29, 31, 33	15-19, 21-22, 24-25
11. Transportation	48-50	60-64
12. Services	45-47, 51-57	45, 50-59, 70-99

3.B Structure and Specification of Theoretical Model

3.B.1 Production

1) Production technology

The representative firm in each production sector has a separable KLEM-H nested CES function, with the following production technology:

$$Q_i = A_i^Q \cdot \left[(\delta_{iz}^Q)^{\frac{1}{\sigma_i^Q}} \cdot Z_i^{\frac{\sigma_i^Q - 1}{\sigma_i^Q}} + (\delta_{ih}^Q)^{\frac{1}{\sigma_i^Q}} \cdot H_i^{\frac{\sigma_i^Q - 1}{\sigma_i^Q}} \right]^{\frac{\sigma_i^Q}{\sigma_i^Q - 1}}$$

$$Z_i = A_i^Z \cdot \left\{ \left[\sum_{j=L,E,M} (\delta_{ij}^Z)^{\frac{1}{\sigma_i^Z}} \cdot X_{ij}^{\frac{\sigma_i^Z - 1}{\sigma_i^Z}} \right] + (\delta_{iK}^Z)^{\frac{1}{\sigma_i^Z}} \cdot K_i^{\frac{\sigma_i^Z - 1}{\sigma_i^Z}} \right\}^{\frac{\sigma_i^Z}{\sigma_i^Z - 1}}$$

$$X_{iE} = A_i^E \cdot \left[\sum_{j=1,\dots,5} (\delta_{ij}^E)^{\frac{1}{\sigma_i^E}} \cdot (X_{ij}^E)^{\frac{\sigma_i^E - 1}{\sigma_i^E}} \right]^{\frac{\sigma_i^E}{\sigma_i^E - 1}}$$

$$X_{iM} = A_i^M \cdot \left[\sum_{j=6,\dots,12} (\delta_{ij}^M)^{\frac{1}{\sigma_i^M}} \cdot (X_{ij}^M)^{\frac{\sigma_i^M - 1}{\sigma_i^M}} \right]^{\frac{\sigma_i^M}{\sigma_i^M - 1}}$$

By the principle of duality, the dual cost functions corresponding to each quantity variable are derived as follows:

$$P_i = (A_i^Q)^{-1} \cdot \left[\delta_{iz}^Q \cdot (P_{iZ})^{1-\sigma_i^Q} + \delta_{ih}^Q \cdot (P_{iH})^{1-\sigma_i^Q} \right]^{\frac{1}{1-\sigma_i^Q}}$$

$$P_{iZ} = (A_i^Z)^{-1} \cdot \left\{ \left[\sum_{j=L,E,M} \delta_{ij}^Z \cdot (P_{ij})^{1-\sigma_i^Z} \right] + \delta_{ik}^Z \cdot (P_{iK})^{1-\sigma_i^Z} \right\}^{\frac{1}{1-\sigma_i^Z}}$$

$$P_{iE} = (A_i^E)^{-1} \cdot \left[\sum_{j=1,\dots,5} \delta_{ij}^E \cdot (P_{ij}^E)^{1-\sigma_i^E} \right]^{\frac{1}{1-\sigma_i^E}}$$

$$P_{iM} = (A_i^M)^{-1} \cdot \left[\sum_{j=6,\dots,12} \delta_{ij}^M \cdot (P_{ij}^M)^{1-\sigma_i^M} \right]^{\frac{1}{1-\sigma_i^M}}$$

where Q_i, P_i are the quantity and price of domestically-produced good, Z_i, P_{iZ} are the quantity and price of physical inputs composite, $\mathbf{X}_i = [X_{iL}, X_{iE}, X_{iM}, K_i, H_i]$, $\mathbf{P}_i = [P_{iL}, P_{iE}, P_{iM}, P_{iK}, P_{iH}]$ are quantity and price of labor, energy bundle, materials bundle, physical capital and knowledge capital. X_{ij}^E, P_{ij}^E are the quantity and price of intermediate energy commodities, X_{ij}^M, P_{ij}^M are the quantity and price of intermediate material commodities.

2) Producer Problem

For each production sector i, the problem of a representative producer is specified as .

$$\max \; V_i(t) = \int_t^{\infty} \exp\left[-\int_t^{s} r(s')\cdot ds'\right]\cdot \Pi_i(s)\cdot ds$$

$$\begin{aligned}
\text{s.t. } \Pi_i(t) &= (1-\tau_Q)\cdot[P_i(t)\cdot Q_i(t) - P_{iL}(t)\cdot X_{iL}(t) - P_{iE}(t)\cdot X_{iE}(t) - P_{iM}(t)\cdot X_{iM}(t)] \\
&\quad - (1-\tau_I)\cdot P_{iI}(t)\cdot I_i(t) - (1-\tau_R)\cdot P_{iR}(t)\cdot R_i(t) \\
\dot{K}_i(t) &= J_i(t) - \delta_K\cdot K_i(t) \\
I_i(t) &= \varphi_i(J_i(t), K_i(t)) = J_i(t) + \frac{\psi}{2}\cdot\frac{J_i(t)^2}{K_i(t)} \\
\dot{H}_i(t) &= \eta\cdot R_i(t)^{\alpha}\cdot H_i(t)^{\beta} + \frac{R_i(t)}{\sum_j R_j(t)}\cdot\left[\theta\cdot\sum_j R_j(t) - R_i(t)\right] - \delta_H\cdot H_i(t)
\end{aligned}$$

The dynamic optimization problem is solved by using the current-value Hamiltonian formulas:

$$\begin{aligned}
\Gamma_i(t) &= (1-\tau_Q)\cdot[P_i(t)\cdot Q_i(t) - P_{iL}(t)\cdot X_{iL}(t) - P_{iE}(t)\cdot X_{iE}(t) - P_{iM}(t)\cdot X_{iM}(t)] \\
&\quad - (1-\tau_I)\cdot P_{iI}(t)\cdot\left(J_i(t) + \frac{\psi}{2}\cdot\frac{J_i(t)^2}{K_i(t)}\right) + \lambda_{iK}(t)\cdot[J_i(t) - \delta_K\cdot K_i(t)] \\
&\quad - (1-\tau_R)\cdot P_{iR}(t)\cdot R_i(t) + \lambda_{iH}(t)\cdot\left\{\eta\cdot R_i(t)^{\alpha}\cdot H_i(t)^{\beta} + \frac{R_i(t)}{\sum_j R_j(t)}\cdot\left[\theta\cdot\sum_j R_j(t) - R_i(t)\right] - \delta_H\cdot H_i(t)\right\}
\end{aligned}$$

We first optimally solve for the demand for labor $X_{iL}(t)$, energy bundle $X_{iE}(t)$ and materials bundle $X_{iM}(t)$ from the F.O.C. with respect to $X_{ij}(t)$ for $j = L,E,M$.

$$\frac{\partial\Gamma_i(t)}{\partial X_{ij}(t)} = P_i(t)\cdot\frac{\partial Q_i(t)}{\partial X_{ij}(t)} - P_{ij}(t) = 0$$

$$\Rightarrow \frac{P_{ij}(t)}{P_i(t)} = \frac{\partial Q_i(t)}{\partial X_{ij}(t)} = \frac{\partial Q_i(t)}{\partial Z_i(t)}\cdot\frac{\partial Z_i(t)}{\partial X_{ij}(t)} = \left[\delta_{iz}^{Q}\cdot(A_i^{Q})^{\sigma_i^Q-1}\cdot\frac{Q_i(t)}{Z_i(t)}\right]^{\frac{1}{\sigma_i^Q}}\cdot\left[\delta_{ij}^{Z}\cdot(A_i^{Z})^{\sigma_i^Z-1}\cdot\frac{Z_i(t)}{X_{ij}(t)}\right]^{\frac{1}{\sigma_i^Z}}$$

where we further use the optimality condition at tier one in the nested CES structure - the value of marginal product of physical input composite $Z_i(t)$ should equal its cost, and obtain the optimal level of demand for physical input composite as follows:

$$P_i(t)\cdot\frac{\partial Q_i(t)}{\partial Z_i(t)} - P_{iZ}(t) = 0 \quad\Rightarrow\quad Z_i(t) = (A_i^{Q})^{\sigma_i^Q-1}\cdot\delta_{iz}^{Q}\cdot\left(\frac{P_i(t)}{P_{iZ}(t)}\right)^{\sigma_i^Q}\cdot Q_i(t)$$

By substituting out Z_i, we derive the optimal level of demand for X_{ij} as function of Q_i:

$$X_{ij}(t) = \left[\delta_{ij}^{Z}\cdot(A_i^{Z})^{\sigma_i^Z-1}\cdot\left(\frac{P_{iZ}(t)}{P_{ij}(t)}\right)^{\sigma_i^Z}\right]\cdot\left[\delta_{iZ}^{Z}\cdot(A_i^{Q})^{\sigma_i^Q-1}\cdot\left(\frac{P_i(t)}{P_{iZ}(t)}\right)^{\sigma_i^Q}\right]\cdot Q_i(t)$$

In the second step, we solve for the optimal level of demand for raw investment goods J_i and R&D goods R_i, and obtain the following optimality conditions for investment and R&D:

$$\frac{\partial \Gamma_i(t)}{\partial J_i(t)} = -(1-\tau_I)\cdot P_{iI}(t)\cdot\left(1+\psi\cdot\frac{J_i(t)}{K_i(t)}\right)+\lambda_{iK}(t)=0$$

$$\Rightarrow\; J_i(t)=\left[\frac{\lambda_{iK}(t)}{(1-\tau_I)\cdot P_{iI}(t)}-1\right]\cdot\frac{K_i(t)}{\psi}$$

$$\frac{\partial \Gamma_i(t)}{\partial R_i(t)} = -(1-\tau_R)\cdot P_{iI}(t)+\lambda_{iH}(t)\cdot\left[a\cdot\eta\cdot R_i(t)^{a-1}\cdot H_i(t)^{\beta}+\theta-\frac{2R_i(t)}{\sum_j R_j(t)}\right]$$

$$\Rightarrow\; (1-\tau_R)\cdot P_{iI}(t)=\lambda_{iH}(t)\cdot\left[a\cdot\eta\cdot R_i(t)^{a-1}\cdot H_i(t)^{\beta}+\theta-\frac{2R_i(t)}{\sum_j R_j(t)}\right]$$

where the above equations are static form of optimality conditions, the truly intertemporal part of this problem is solved by optimally choosing the dynamic paths for the shadow price of physical and knowledge capital λ_{iK} λ_{iH}:

$$\dot{\lambda}_{iK}(t)-r(t)\cdot\lambda_{iK}(t)=-\frac{\partial \Gamma_i(t)}{\partial K_i(t)}=-(1-\tau_Q)\cdot P_i(t)\cdot\frac{\partial Q_i(t)}{\partial K_i(t)}-(1-\tau_I)\cdot P_{iI}(t)\cdot\frac{\psi}{2}\cdot\left(\frac{J_i(t)}{K_i(t)}\right)^2+\delta_K\cdot\lambda_{iK}(t)$$

$$\Rightarrow\;\frac{\dot{\lambda}_{iK}(t)+(1-\tau_Q)\cdot P_i(t)\cdot\frac{\partial Q_i(t)}{\partial K_i(t)}+(1-\tau_I)\cdot P_{iI}(t)\cdot\frac{\psi}{2}\cdot\left(\frac{J_i(t)}{K_i(t)}\right)^2}{\lambda_{iK}(t)}=r(t)+\delta_K$$

where the expression denotes an implicit arbitrage condition for physical capital investment: LHS denotes the shadow rate of return from an extra unit of investment in physical capital, including: the increase in the shadow price of physical capital, marginal product of physical capital, and the adjustment cost saving. RHS represents the cost of physical capital investment, including the market interest rate and the capital depreciation rate. Hence, in determining the optimal path of λ_{iK}, the firm is guided by this implicit arbitrage equation. In a similar way, we can solve for the optimal dynamic path for the shadow price of knowledge asset λ_{iH}.

$$\dot{\lambda}_{iH}(t)-r(t)\cdot\lambda_{iH}(t)=-\frac{\partial \Gamma_i(t)}{\partial H_i(t)}$$

$$\Rightarrow\;\frac{\dot{\lambda}_{iH}(t)+(1-\tau_Q)\cdot P_i(t)\cdot\frac{\partial Q_i(t)}{\partial H_i(t)}+\lambda_{iH}(t)\cdot\eta\cdot\beta\cdot R_i(t)^{a}\cdot H_i(t)^{\beta-1}}{\lambda_{iH}(t)}=r(t)+\delta_H$$

3) Characterization of Producer Problem

- For any production sector i $(i=1,\dots,12)$, the optimal level of demand for labor, energy bundle and materials bundle are characterized as follows:

$$X_{iL}(t)=\left[\delta_{iL}^{Z}\cdot(A_i^{Z})^{\sigma_i^Z-1}\cdot\left(\frac{P_{iZ}(t)}{P_{iL}(t)}\right)^{\sigma_i^Z}\right]\cdot\left[\delta_{iZ}^{Z}\cdot(A_i^{Q})^{\sigma_i^Q-1}\cdot\left(\frac{P_i(t)}{P_{iZ}(t)}\right)^{\sigma_i^Q}\right]\cdot Q_i(t)$$

$$X_{iE}(t)=\left[\delta_{iE}^{Z}\cdot(A_i^{Z})^{\sigma_i^Z-1}\cdot\left(\frac{P_{iZ}(t)}{P_{iE}(t)}\right)^{\sigma_i^Z}\right]\cdot\left[\delta_{iZ}^{Z}\cdot(A_i^{Q})^{\sigma_i^Q-1}\cdot\left(\frac{P_i(t)}{P_{iZ}(t)}\right)^{\sigma_i^Q}\right]\cdot Q_i(t)$$

$$X_{iM}(t)=\left[\delta_{iM}^{Z}\cdot(A_i^{Z})^{\sigma_i^Z-1}\cdot\left(\frac{P_{iZ}(t)}{P_{iM}(t)}\right)^{\sigma_i^Z}\right]\cdot\left[\delta_{iZ}^{Z}\cdot(A_i^{Q})^{\sigma_i^Q-1}\cdot\left(\frac{P_i(t)}{P_{iZ}(t)}\right)^{\sigma_i^Q}\right]\cdot Q_i(t)$$

where the optimal demands for energy bundle X_{iE} and materials bundle X_{iM} are further disaggregated into demand for each energy commodities X_{ij}^{E} and material commodities X_{ij}^{M} as:

$$X_{ij}^{E}(t)=\left[\delta_{ij}^{E}\cdot(A_i^{E})^{\sigma_i^E-1}\cdot\left(\frac{P_{iE}(t)}{P_{ij}^{E}(t)}\right)^{\sigma_i^E}\right]\cdot X_{iE}(t)$$

$$X_{ij}^{M}(t)=\left[\delta_{ij}^{M}\cdot(A_i^{M})^{\sigma_i^M-1}\cdot\left(\frac{P_{iM}(t)}{P_{ij}^{M}(t)}\right)^{\sigma_i^M}\right]\cdot X_{iM}(t)$$

- Investment behavior of producer is characterized by the following conditions:

$$J_i(t)=\left[\frac{\lambda_{iK}(t)}{(1-\tau_I)\cdot P_{iI}(t)}-1\right]\cdot\frac{K_i(t)}{\psi}$$

$$\frac{\dot{\lambda}_{iK}(t)+(1-\tau_Q)\cdot P_i(t)\cdot\dfrac{\partial Q_i(t)}{\partial K_i(t)}+(1-\tau_I)\cdot P_{iI}(t)\cdot\dfrac{\psi}{2}\cdot\left(\dfrac{J_i(t)}{K_i(t)}\right)^2}{\lambda_{iK}(t)}=r(t)+\delta_K$$

$$I_i(t)=J_i(t)+\frac{\psi}{2}\cdot\frac{J_i(t)^2}{K_i(t)}$$

$$\dot{K}_i(t)=J_i(t)-\delta_K\cdot K_i(t)$$

where the first term is the static optimality conditions for investment determined by the shadow price of physical capital.. The second is the implicit arbitrage condition that determines the time path of the shadow price of physical capital. The third denotes the actual purchases of investment goods with adjustment cost function. The fourth is the law of motion of physical capital stock.

- R&D behavior of producer is characterized by the following conditions:

$$(1-\tau_R)\cdot P_{iR}(t)=\lambda_{iH}(t)\cdot\left[a\cdot\eta\cdot R_i(t)^{a-1}\cdot H_i(t)^{\beta}+\theta-\frac{2R_i(t)}{\sum_j R_j(t)}\right]$$

$$\frac{\dot{\lambda}_{iH}(t)+(1-\tau_Q)\cdot P_i(t)\cdot\dfrac{\partial Q_i(t)}{\partial H_i(t)}+\lambda_{iH}(t)\cdot\eta\cdot\beta\cdot R_i(t)^{a}\cdot H_i(t)^{\beta-1}}{\lambda_{iH}(t)}=r(t)+\delta_H$$

$$\dot{H}_i(t)=\eta\cdot R_i(t)^{a}\cdot H_i(t)^{\beta}+\frac{R_i(t)}{\sum_j R_j(t)}\cdot\left[\theta\cdot\sum_j R_j(t)-R_i(t)\right]-\delta_H\cdot H_i(t)$$

where the first term is the optimality conditions for R&D investment determined by the shadow price of knowledge stock. The second is the implicit arbitrage condition that determines the time path for the shadow price of knowledge asset. The third denotes the *innovation possibility frontier* for knowledge creation.

3.B.2. Consumption

1) Structure of Consumption

In each economy, we assume a representative household owns all factors of production and all shares in firms, and determine the consumption which is a CES aggregate of individual consumption goods:

$$C=\left[\sum_{j=E,M}\left(\delta_{Cj}^{O}\right)^{\frac{1}{\sigma_C^O}}\cdot\left(X_{Cj}\right)^{\frac{\sigma_C^O-1}{\sigma_C^O}}\right]^{\frac{\sigma_C^O}{\sigma_C^O-1}}$$

$$X_{CE}=\left[\sum_{j=1,\dots,5}\left(\delta_{Cj}^{E}\right)^{\frac{1}{\sigma_C^E}}\cdot\left(X_{Cj}^{E}\right)^{\frac{\sigma_C^E-1}{\sigma_C^E}}\right]^{\frac{\sigma_C^E}{\sigma_C^E-1}}$$

$$X_{CM}=\left[\sum_{j=6,\dots,12}\left(\delta_{Cj}^{M}\right)^{\frac{1}{\sigma_C^M}}\cdot\left(X_{Cj}^{M}\right)^{\frac{\sigma_C^M-1}{\sigma_C^M}}\right]^{\frac{\sigma_C^M}{\sigma_C^M-1}}$$

The dual cost functions corresponding to each above variable are as follows

$$P_C=\left[\sum_{j=E,M}\delta_{Cj}^{O}\cdot\left(P_{Cj}\right)^{1-\sigma_C^O}\right]^{\frac{1}{1-\sigma_C^O}}$$

$$P_{CE}=\left[\sum_{j=1,\dots,5}\delta_{Cj}^{E}\cdot\left(P_{Cj}^{E}\right)^{1-\sigma_C^E}\right]^{\frac{1}{1-\sigma_C^E}}$$

$$P_{CM}=\left[\sum_{j=6,\dots,12}\delta_{Cj}^{M}\cdot\left(P_{Cj}^{M}\right)^{1-\sigma_C^M}\right]^{\frac{1}{1-\sigma_C^M}}$$

where C,P_C are aggregate consumption and consumer price index, $\mathbf{X}_C=[X_{CE},X_{CM}]$, $\mathbf{P}_C=[P_{CE},P_{CM}]$ are the consumed quantity and consumer price of energy bundle and materials bundle. X_{Cj}^{E},P_{Cj}^{E} are the consumed quantity and consumer price of energy commodities, X_{Cj}^{M},P_{Cj}^{M} are the consumed quantity and consumer price of material commodities.

2) Consumer Problem

The consumer problem is to maximize an intertemporal utility subject to the budget constraint and transversality condition:

$$\max\ U(t)=\int_t^{\infty}\ln C(s)\cdot\exp[-\rho\cdot(s-t)]\cdot ds$$
$$\text{s.t. } P_C(s)\cdot C(s)+\dot{A}(s)=r(s)\cdot A(s)+w(s)\cdot L(s)$$
$$\lim_{s\to\infty}A(s)\cdot\exp\left[-\int_t^s r(s')\cdot ds'\right]=0$$

By integrating the static budget constraint over an infinite time horizon, we can derive a lifetime budget constraint where the discounted present value of future consumption expenditure is financed by the sum of human wealth and financial wealth:

$$\int_t^{\infty}P_C(s)\cdot C(s)\cdot\exp\left[-\int_t^s r(s')\cdot ds'\right]\cdot ds=H_C(t)+A_C(t)$$
$$\text{with}\quad H_C(t)=\int_t^{\infty}(1-\tau_w)\cdot w(s)\cdot L(s)\cdot\exp\left[-\int_t^s r(s')\cdot ds'\right]\cdot ds$$
$$A_C(t)=\sum_i[\lambda_{iK}(t)\cdot K_i(t)+\lambda_{iH}(t)\cdot H_i(t)]$$

where C, P_C are aggregate consumption level and consumer price index, respectively. H_C denotes the human wealth as the discounted present value of future income stream. The labor income is made up of after-tax wage earnings $(1-\tau_w)\cdot w(s)\cdot L(s)$. The financial wealth $A_C(t)$ involves the equity values hold by the representative household, equaling the stock market value of physical assets $\lambda_K\cdot K$ and knowledge assets $\lambda_H\cdot H$.

The consumer problem can be solved by constructing the Lagrangian as follows:

$$L(t)=\int_t^{\infty}\ln C(s)\cdot\exp[-\rho\cdot(s-t)]\cdot ds+\lambda(t)\cdot\left(H_C(t)+A_C(t)-\int_t^{\infty}P_C(s)\cdot C(s)\cdot\exp\left[-\int_t^s r(s')\cdot ds'\right]\cdot ds\right)$$

F.O.C. with respect to $C(s)$ yields:

$$\frac{1}{C(s)}\cdot\exp[-\rho\cdot(s-t)]-\lambda(t)\cdot\left(P_C(s)\cdot\exp\left[\int_t^s r(s')\cdot ds'\right]\right)=0\Rightarrow P_C(s)\cdot C(s)=\frac{1}{\lambda(t)}\cdot\exp[-\rho\cdot(s-t)]\cdot\exp\left[\int_t^s r(s')\cdot ds'\right]$$

Plug back into the lifetime budget constraint yields:

$$H_C(t)+A_C(t)=\int_t^{\infty}P_C(s)\cdot C(s)\cdot\exp\left[-\int_t^s r(s')\cdot ds'\right]\cdot ds$$
$$=\int_t^{\infty}\frac{1}{\lambda(t)}\cdot\exp[-\rho\cdot(s-t)]\cdot\exp\left[\int_t^s r(s')\cdot ds'\right]\cdot\exp\left[-\int_t^s r(s')\cdot ds'\right]\cdot ds$$
$$=\int_t^{\infty}\frac{1}{\lambda(t)}\cdot\exp[-\rho\cdot(s-t)]\cdot ds\ =\ \frac{1}{\lambda(t)}\cdot\frac{1}{\rho}$$
$$\Rightarrow\quad \rho\cdot(H_C(t)+A_C(t))=\frac{1}{\lambda(t)}$$
$$\Rightarrow\quad P_C(s)\cdot C(s)=\rho\cdot(H_C(t)+A_C(t))\cdot\exp[-\rho\cdot(s-t)]\cdot\exp\left[\int_t^s r(s')\cdot ds'\right]$$

Given the human and financial wealth at time t, the household will choose her optimal consumption path over time $s=[t,t+1,...,\infty]$ according to the above equation. Let s=t and derive the optimal consumption level at current period:

$$P_C(s)\cdot C(s)=\rho\cdot(H_C(t)+A_C(t))$$

This formula represents the consumption behavior of household according to permanent income hypothesis - household's consumption expenditure equals to a constant proportion of the aggregated human and financial wealth. But some group of household are liquidity-constrained with myopic expectations about her future income, and are only able to consume a fraction of the after-tax income given by exogenous propensity to consume σ. The aggregate consumption expenditure $P_C\cdot C$ is expressed as a weighted average of neoclassical optimizing behavior and liquidity-constrained behaviors as follows:

$$P_C(t)\cdot C(t)=\theta\cdot\rho\cdot[H_C(t)+A_C(t)]+(1-\theta)\cdot\sigma\cdot w(s)\cdot L(s)$$

Based on the two-tier nested CES structure of consumption, the aggregate consumption expenditure can be allocated to each goods and services component:

$$P_{Cj}(t)\cdot X_{Cj}(t)=\left[\delta_{Cj}^{O}\cdot\left(\frac{P_C(t)}{P_{Cj}(t)}\right)^{\sigma_C^O-1}\right]\cdot P_C(t)\cdot C(t)\qquad j=E,M$$

$$P_{Cj}^{E}(t)\cdot X_{Cj}^{E}(t)=\left[\delta_{Cj}^{E}\cdot\left(\frac{P_{CE}(t)}{P_{Cj}^{E}(t)}\right)^{\sigma_C^E-1}\right]\cdot P_{CE}(t)\cdot X_{CE}(t)\qquad j=1,...,5$$

$$P_{Cj}^{M}(t)\cdot X_{Cj}^{M}(t)=\left[\delta_{Cj}^{M}\cdot\left(\frac{P_{CM}(t)}{P_{Cj}^{M}(t)}\right)^{\sigma_C^M-1}\right]\cdot P_{CM}(t)\cdot X_{CM}(t)\qquad j=6,...,12$$

where $\mathbf{P}_{Cj}(t)\cdot\mathbf{X}_{Cj}(t)=[P_{CE}(t)\cdot X_{CE}(t),P_{CM}(t)\cdot X_{CM}(t)]$ are the consumption expenditure on energy and material bundles. $P_{Cj}^{E}(t)\cdot X_{Cj}^{E}(t)$ are the consumption expenditure on energy commodities, $P_{Cj}^{M}(t)\cdot X_{Cj}^{M}(t)$ are the consumption expenditure on material commodities

3) Characterization of Consumer Problem

- From labor endowment, human and financial wealth, aggregate consumption expenditures are determined:

$$P_C(t)\cdot C(t)=\theta\cdot\rho\cdot[H_C(t)+A_C(t)]+(1-\theta)\cdot\sigma\cdot w(s)\cdot L(s)$$

$$H_C(t)=\int_t^{\infty}(1-\tau_w)\cdot w(s)\cdot L(s)\cdot\exp\left[-\int_t^{s}r(s')\cdot ds'\right]\cdot ds$$

$$A_C(t)=\sum_{i=1,\ldots,12}[\lambda_{iK}(t)\cdot K_i(t)+\lambda_{iH}(t)\cdot H_i(t)]$$

- Aggregate consumption expenditure is allocated into individual E/M commodities as:

$$X_{CE}(t)=\left[\delta_{CE}^{Q}\cdot\left(\frac{P_C(t)}{P_{CE}(t)}\right)^{\sigma_C^Q}\right]\cdot C(t)$$

$$X_{CM}(t)=\left[\delta_{CM}^{Q}\cdot\left(\frac{P_C(t)}{P_{CM}(t)}\right)^{\sigma_C^Q}\right]\cdot C(t)$$

where the demand for energy bundle $X_{CE}(t)$ and materials bundle $X_{CM}(t)$ is further allocated into each energy commodities $X_{Cj}^{E}(t)$ $j=1,\ldots,5$ and material commodities $X_{Cj}^{M}(t)$ $j=6,\ldots,12$:

$$X_{Cj}^{E}(t)=\left[\delta_{Cj}^{E}\cdot\left(\frac{P_{CE}(t)}{P_{Cj}^{E}(t)}\right)^{\sigma_C^E}\right]\cdot X_{CE}(t)$$

$$X_{Cj}^{M}(t)=\left[\delta_{Cj}^{M}\cdot\left(\frac{P_{CM}(t)}{P_{Cj}^{M}(t)}\right)^{\sigma_C^E}\right]\cdot X_{CM}(t)$$

3.B.3 Capital good producing sector

The investment sector produces new investment goods by combining energy and materials according to a two-tier nested CES production technology:

$$Q_I=A_I^Q\left[\sum_{j=E,M}(\delta_{Ij}^{Q})^{\frac{1}{\sigma_I^Q}}\cdot(X_{Ij})^{\frac{\sigma_I^Q-1}{\sigma_I^Q}}\right]^{\frac{\sigma_I^Q}{\sigma_I^Q-1}}$$

$$X_{IE}=A_I^E\cdot\left[\sum_{j=1,\ldots,5}(\delta_{Ij}^{E})^{\frac{1}{\sigma_I^E}}\cdot(X_{Ij}^{E})^{\frac{\sigma_I^E-1}{\sigma_I^E}}\right]^{\frac{\sigma_I^E}{\sigma_I^E-1}}$$

$$X_{IM}=A_I^M\cdot\left[\sum_{j=6,\ldots,12}(\delta_{Ij}^{M})^{\frac{1}{\sigma_I^M}}\cdot(X_{Ij}^{M})^{\frac{\sigma_I^M-1}{\sigma_I^M}}\right]^{\frac{\sigma_I^M}{\sigma_I^M-1}}$$

The dual cost function corresponding to each variable is as follows:

$$P_I=(A_I^Q)^{-1}\cdot\left[\sum_{j=E,M}\delta_{Ij}^{Q}\cdot(P_{Ij})^{1-\sigma_I^Q}\right]^{\frac{1}{1-\sigma_I^Q}}$$

$$P_{IE}=(A_I^E)^{-1}\cdot\left[\sum_{j=1,\ldots,5}\delta_{Ij}^{E}\cdot(P_{Ij}^{E})^{1-\sigma_I^E}\right]^{\frac{1}{1-\sigma_I^E}}$$

$$P_{IM}=(A_I^M)^{-1}\cdot\left[\sum_{j=6,\ldots,12}\delta_{Ij}^{M}\cdot(P_{Ij}^{M})^{1-\sigma_I^M}\right]^{\frac{1}{1-\sigma_I^M}}$$

where Q_I, P_I are the quantity and price of investment good, $\mathbf{X}_I = [X_{IE}, X_{IM}], \mathbf{P}_I = [P_{IE}, P_{IM}]$ are quantity and price of E/M bundle used in financial sector. X_{Ij}^E, P_{Ij}^E are the quantity and price of energy commodities, X_{Ij}^M, P_{Ij}^M are the quantity and price of material commodities.

For the investment sectors, the producer problem is specified as:

$$\max \ \prod_I(t) = P_I(t) \cdot Q_I(t) - P_{IE}(t) \cdot X_{IE}(t) - P_{IM}(t) \cdot X_{IM}(t)$$

where the firm's objective is to optimally choose the inputs of energy bundle X_{IE} and materials bundle X_{IM} for maximizing its current profit flows $\prod_I$. Solving this top-tier static maximization problem can determine the demands for the inputs of energy and materials bundles. We further solve a cost minimization problem at energy and material tier, and characterize the demand for each individual energy and material commodities.

The optimal level of demand for energy bundles and materials bundles are characterized as:

$$X_{IE}(t) = \delta_{IE}^Q \cdot \left(A_I^Q\right)^{\sigma_I^Q - 1} \cdot \left(\frac{P_I(t)}{P_{IE}(t)}\right)^{\sigma_I^Q} \cdot Q_I(t)$$

$$X_{IM}(t) = \delta_{IM}^Q \cdot \left(A_I^Q\right)^{\sigma_I^Q - 1} \cdot \left(\frac{P_I(t)}{P_{IM}(t)}\right)^{\sigma_I^Q} \cdot Q_I(t)$$

where the demand for energy bundle X_{IE} and materials bundle X_{IM} is further disaggregated into each energy commodities $X_{Ij}^E \quad j = 1,...,5$ and material commodities $X_{Ij}^M \quad j = 6,...,12$:

$$X_{Ij}^E(t) = \delta_{Ij}^E \cdot \left(A_I^E\right)^{\sigma_I^E - 1} \cdot \left(\frac{P_{IE}(t)}{P_{Ij}^E(t)}\right)^{\sigma_I^E} \cdot X_{IE}(t)$$

$$X_{Ij}^M(t) = \delta_{Ij}^M \cdot \left(A_I^M\right)^{\sigma_I^M - 1} \cdot \left(\frac{P_{IM}(t)}{P_{Ij}^M(t)}\right)^{\sigma_I^M} \cdot X_{IM}(t)$$

3.B.4 R&D good producing sector

The structure of production technology in R&D sector is to produce R&D goods by combining energy and material bundles according to a two-tier nested CES function.

$$Q_R = A_R^Q \cdot \left[\sum\nolimits_{j=E,M} (\delta_{Rj}^Q)^{\frac{1}{\sigma_R^Q}} \cdot (X_{Rj})^{\frac{\sigma_R^Q-1}{\sigma_R^Q}}\right]^{\frac{\sigma_R^Q}{\sigma_R^Q-1}}$$

$$X_{RE} = A_R^E \cdot \left[\sum\nolimits_{j=1,\dots,5} (\delta_{Rj}^E)^{\frac{1}{\sigma_R^E}} \cdot (X_{Rj}^E)^{\frac{\sigma_R^E-1}{\sigma_R^E}}\right]^{\frac{\sigma_R^E}{\sigma_R^E-1}}$$

$$X_{RM} = A_R^M \cdot \left[\sum\nolimits_{j=6,\dots,12} (\delta_{Rj}^M)^{\frac{1}{\sigma_R^M}} \cdot (X_{Rj}^M)^{\frac{\sigma_R^M-1}{\sigma_R^M}}\right]^{\frac{\sigma_R^M}{\sigma_R^M-1}}$$

By the principle of duality, the dual cost function can be expressed as follows:

$$P_R = (A_R^Q)^{-1} \cdot \left[\sum\nolimits_{j=E,M} \delta_{Rj}^Q \cdot (P_{Rj})^{1-\sigma_R^Q}\right]^{\frac{1}{1-\sigma_R^Q}}$$

$$P_{RE} = (A_R^E)^{-1} \left[\sum\nolimits_{j=1,\dots,5} \delta_{Rj}^E \cdot (P_{Rj}^E)^{1-\sigma_R^E}\right]^{\frac{1}{1-\sigma_R^E}}$$

$$P_{RM} = (A_R^M)^{-1} \cdot \left[\sum\nolimits_{j=6,\dots,12} \delta_{Rj}^M \cdot (P_{Rj}^M)^{1-\sigma_R^M}\right]^{\frac{1}{1-\sigma_R^M}}$$

where Q_R, P_R are the quantity and price of produced R&D good, $\mathbf{X_R} = [X_{IE}, X_{IM}]$, $\mathbf{P_R} = [P_{IE}, P_{IM}]$ are quantity and price of capital service, labor, energy and materials used in R&D sector. X_{Rj}^E, P_{Rj}^E are the quantity and price of energy commodities, X_{Rj}^M, P_{Rj}^M are the quantity and price of material commodities.

For R&D sectors, the producer problem is specified as follows:

$$\max \ \Pi_R(t) = P_R(t) \cdot Q_R(t) - P_{RE}(t) \cdot X_{RE}(t) - P_{RM}(t) \cdot X_{RM}(t)$$

where the firm's objective is to optimally choose the inputs of energy bundle X_{RE} and materials bundle X_{RM} for maximizing its current profit flows Π_R. Solving this top-tier static maximization problem can determine the demands for the inputs of energy and materials bundles. We further solve a cost minimization problem at energy and material tier, and characterize the demand for each individual energy and material commodities. The optimal level of demand for energy bundles and materials bundles are characterized as :

$$X_{RE}(t) = \delta_{RE}^Q \cdot (A_R^Q)^{\sigma_R^Q-1} \cdot \left(\frac{P_R(t)}{P_{RE}(t)}\right)^{\sigma_R^Q} \cdot Q_R(t)$$

$$X_{RM}(t) = \delta_{RM}^Q \cdot (A_R^Q)^{\sigma_R^Q-1} \cdot \left(\frac{P_R(t)}{P_{RM}(t)}\right)^{\sigma_R^Q} \cdot Q_R(t)$$

where the demand for energy X_{RE} and materials bundle X_{RM} is disaggregated into each energy good X_{Rj}^E $j = 1,\dots,5$ and material good X_{Rj}^M $j = 6,\dots,12$:

$$X_{Rj}^{E}(t)=\delta_{Rj}^{E}\cdot\left(A_{R}^{E}\right)^{\sigma_{R}^{E}-1}\cdot\left(\frac{P_{RE}(t)}{P_{Rj}^{E}(t)}\right)^{\sigma_{R}^{E}}\cdot X_{RE}(t)$$

$$X_{Rj}^{M}(t)=\delta_{Rj}^{M}\cdot\left(A_{R}^{M}\right)^{\sigma_{R}^{M}-1}\cdot\left(\frac{P_{RM}(t)}{P_{Rj}^{M}(t)}\right)^{\sigma_{R}^{M}}\cdot X_{RM}(t)$$

3.B.5 Government

Government behavior is normally constrained by a specific budgetary regime, which is represented by a certain well-defined fiscal target. The target of the Chinese government is to ensure a balanced budget with public revenue neutrality (NBS, 2010). Thus, our model specifies the government behavior as follows: it collects the revenue of tax imposed on corporate profit, household income and fossil energy use to finance public expenditure and subsidies on private investment and R&D:

$$G(t)=T_{Q}(t)+T_{W}(t)+T_{C}(t)-T_{I}(t)-T_{R}(t)$$

where G is aggregate government expenditure for the current use of goods and services. This aggregate spending is then allocated among individual energy and material goods according to historical spending shares. Tax revenue is collected from corporate profit T_Q, household income T_W and carbon emissions T_C. T_I, T_R denote government spending on subsidizing private investment and R&D, respectively. The government budget constraint is hereby determined by endogenous economic activities of private agents and exogenous tax rates setting.

According to historical spending shares, aggregate government expenditure is allocated among individual commodities, and yield government demands for each energy good $X_{Gj}^{E}(t)$ $j=1,...,5$ and material good $X_{Gj}^{M}(t)$ $j=6,...,12$:

$$X_{Gj}^{E}(t)=\frac{G_{j}^{E}(0)}{G(0)}\cdot G(t) \qquad j=1,...,5$$

$$X_{Gj}^{M}(t)=\frac{G_{j}^{M}(0)}{G(0)}\cdot G(t) \qquad j=6,...,12$$

where $G(0), G_{j}^{E}(0), G_{j}^{M}(0)$ denote the initial period government aggregate spending, spending on energy goods and spending on material goods, respectively.

3.B.6 International Trade

We model international trade flows in line with the Armington structure: a commodity produced domestically is an imperfect substitute for the imported goods. For any given good, the domestically-produced output is combined with the imports to create a CES Armington composite of that commodity.

$$Y_i(t)=\left[Q_i(t)^{\frac{\sigma_i^Y-1}{\sigma_i^Y}}+M_i(t)^{\frac{\sigma_i^Y-1}{\sigma_i^Y}}\right]^{\frac{\sigma_i^Y}{\sigma_i^Y-1}}$$

where Y_i denote the total supply of Armington composite good i as a CES aggregate of domestically-produced output Q_i and import M_i that is set exogenously. Total supplies of that Armington commodity are used to clear the demands by intermediate production and final use. The export is modeled by allocating each Armington commodity between domestic and export markets via a constant elasticity of transformation (CET) assumption.

$$X_{Xi}(t)=\left(P_i(t)\right)^{\sigma^{CET}}\cdot Y_i(t)$$

where the export X_{Xi} is modeled by allocating Armington composite Y_i to export market according to its product price P_i and CET parameter σ^{CET}.

3.B.7 Market clearing condition

- Market clear condition for each individual commodity j $(j=1,...,12)$

$$Y_j(t)=\sum_i X_{ij}(t)+X_{Cj}(t)+X_{Ij}(t)+X_{Rj}(t)+X_{Gj}(t)+X_{Xj}(t)$$

where the LHS denotes the total supply of Armington goods j $(j=1,...,12)$, which is used to satisfy the RHS demand by production, consumption, investment, R&D, government and export. This market clearing condition thus pins down an equilibrium price of commodity j.

- Market clear condition for raw investment good

$$Q_I(t)=\sum_i I_i(t)$$

where the LHS denotes the total supply of raw investment good (the output produced by investment sector), which is used to satisfy the capital good demand by production sectors in the

RHS. This market clearing condition pins down an equilibrium price of raw investment good.

- Market clear condition for raw R&D goods

$$Q_R(t) = \sum_i R_i(t)$$

where the LHS denotes the total supply of raw R&D goods (the output produced by R&D sector), which is used to satisfy the R&D good demand by production sectors in the RHS. This market clearing condition thus pins down an equilibrium price of raw R&D goods.

- Market clear condition for labor

$$L^S(0) \cdot \exp(n_L \cdot t) = \sum_i X_{iL}(t)$$

where the representative household derives no felicity from leisure and inelastically supplies its labor endowment at a constant exponential rate of growth n_L, with initial period labor endowment $L^S(0)$. The demand side is determined by labor employment in production sectors. Equilibrium closure requires full employment and labor market clearing, which pins down the equilibrium labor wage.

3.C GEMPACK TABLO Model Codes

```
!============================================================================
GEMPACK TABLO code for implementing a single-country endogenous
technical change CGE model as outlined in the thesis Chapter 3
============================================================================!

! Text between exclamation marks is a comment.                           !
! Text between hashes (#) is labelling information.                      !

!==============================================
FILES
==============================================!
FILE BASEDATA # input base data #;

!===========================================
SETS
===========================================!
SET sectors # 12 production sectors #
(a01, a02, a03, a04, a05, a06, a07, a08, a09, a10, a11, a12);
SET sectors_e # 5 energy sectors #
(a01, a02, a03, a04, a05);
SET sectors_m # 7 material sectors #
(a06, a07, a08, a09, a10, a11, a12);
SUBSET sectors_e IS SUBSET OF sectors;
SUBSET sectors_m IS SUBSET OF sectors;

SET goods # 12 commodities #
(g01, g02, g03, g04, g05, g06, g07, g08, g09, g10, g11, g12);
SET goods_e # 5 energy commodities #
(g01, g02, g03, g04, g05);
SET goods_m # 7 material commodities #
(g06, g07, g08, g09, g10, g11, g12);
SUBSET goods_e IS SUBSET OF goods;
SUBSET goods_m IS SUBSET OF goods;

SET
(INTERTEMPORAL) alltime  # all time periods # (p0 - p26);
SET
(INTERTEMPORAL) fwdtime #domain of forward difference #  (p0 - p25);
SET
(INTERTEMPORAL) endtime # ending time# (p26);
SUBSET fwdtime IS SUBSET OF alltime;
SUBSET endtime IS SUBSET OF alltime;

!============================================================================
Data coefficients & variables: Energy commodity flows of IO table
for Production 1, Consumption 2, Investment 3, R&D 4, Gov't 5, Export 6
============================================================================!
Coefficient
(all, j, goods_e) (all, i, sectors) (all, t, alltime)  V1E(j, i, t)
# value: energy commodity into production #;
(all, j, goods_e) (all, t, alltime)  V2E(j, t)
# value: energy commodity into consumption # ;
(all, j, goods_e) (all, t, alltime)  V3E(j, t)
# value: energy commodity into investment #;
(all, j, goods_e) (all, t, alltime)  V4E(j, t)
 # value: energy commodity into R&D #;
(all, j, goods_e) (all, t, alltime)  V5E(j, t)
 # value: energy commodity into gov't #;
(all, j, goods_e) (all, t, alltime)  V6E(j, t)
 # value: energy commodity into export #;

Read
V1E from FILE BASEDATA HEADER "V1E";
V2E from FILE BASEDATA HEADER "V2E";
V3E from FILE BASEDATA HEADER "V3E";
V4E from FILE BASEDATA HEADER "V4E";
```

```
V5E from FILE BASEDATA HEADER "V5E";
V6E from FILE BASEDATA HEADER "V6E";

Variable
(all, j, goods_e) (all, i, sectors) (all, t, alltime)  en(j, i, t)
 # quantity of E commodity into production #;
(all, j, goods_e) (all, t, alltime)   cone(j, t)
 # quantity of E commodity into consumption # ;
(all, j, goods_e) (all, t, alltime)   iine(j, t)
 # quantity of E commodity into investment #;
(all, j, goods_e) (all, t, alltime)   rrne(j, t)
# quantity of E commodity into R&D #;
(all, j, goods_e) (all, t, alltime)   gcee(j, t)
# quantity of E commodity into gov't #;
(all, j, goods_e) (all, t, alltime)   exqe(j, t)
 # quantity of E commodity into export #;
(all, j, goods) (all, t, alltime)   pry(j, t)
# price of both E and M commodity as Armington good#;

Update
(all, j, goods_e) (all, i, sectors) (all, t, alltime)
V1E(j, i, t) = en(j, i, t) * pry(j, t) ;
(all, j, goods_e) (all, t, alltime)
 V2E(j, t) = cone(j, t) * pry(j, t);
(all, j, goods_e) (all, t, alltime)
V3E(j, t) = iine(j, t) * pry(j, t);
(all, j, goods_e) (all, t, alltime)
V4E(j, t) = rrne(j, t) * pry(j, t);
(all, j, goods_e) (all, t, alltime)
V5E(j, t) = gcee(j, t) * pry(j, t);
(all, j, goods_e) (all, t, alltime)
V6E(j, t) = exqe(j, t) * pry(j, t);
!=====================================================================
Data coefficients & variables: Material commodity flows of io table
for Production 1, Consumption 2, Investment 3, R&D 4, Gov't 5, Export 6
=====================================================================!
Coefficient
(all, j, goods_m) (all, i, sectors) (all, t, alltime)  V1M(j,i,t)
# value: M commodity into production #;
(all, j, goods_m) (all, t, alltime)  V2M(j, t)
# value: M commodity into consumption # ;
(all, j, goods_m) (all, t, alltime)  V3M(j, t)
# value: M commodity into investment #;
(all, j, goods_m) (all, t, alltime)  V4M(j, t)
# value: M commodity into R&D #;
(all, j, goods_m) (all, t, alltime)  V5M(j, t)
# value: M commodity into gov't #;
(all, j, goods_m) (all, t, alltime)  V6M(j, t)
# value: M commodity into export #;

Read
V1M from FILE BASEDATA HEADER "V1M";
V2M from FILE BASEDATA HEADER "V2M";
V3M from FILE BASEDATA HEADER "V3M";
V4M from FILE BASEDATA HEADER "V4M";
V5M from FILE BASEDATA HEADER "V5M";
V6M from FILE BASEDATA HEADER "V6M";

Variable
(all, j, goods_m) (all, i, sectors) (all, t, alltime)  oi(j, i, t)
 # quantity of M commodity into production #;
(all, j, goods_m) (all, t, alltime)  cono(j, t)
# quantity of M commodity into consumption # ;
(all, j, goods_m) (all, t, alltime)   iino(j, t)
# quantity of M commodity into investment #;
(all, j, goods_m) (all, t, alltime)   rrno(j, t)
 # quantity of M commodity into R&D #;
(all, j, goods_m) (all, t, alltime)  gceo(j, t)
# quantity of M commodity into gov't #;
(all, j, goods_m) (all, t, alltime)  exqo(j, t)
# quantity of M commodity into export #;
```

```
Update
(all, j, goods_m) (all, i, sectors) (all, t, alltime)
 V1M(j, i, t) = oi(j, i, t)* pry(j, t) ;
(all, j, goods_m) (all, t, alltime)
V2M(j, t) = cono (j, t) * pry(j, t);
(all, j, goods_m) (all, t, alltime)
 V3M(j, t) = iino (j, t) * pry(j, t);
(all, j, goods_m) (all, t, alltime)
V4M(j, t) = rrno (j, t) * pry(j, t);
(all, j, goods_m) (all, t, alltime)
 V5M(j, t) = gceo (j, t) * pry(j, t);
(all, j, goods_m) (all, t, alltime)
 V6M(j, t) = exqo (j, t) * pry(j, t);

!=====================================================================
Data coefficients and variables: Primary factor input into production
=====================================================================!
Coefficient
(all, i, sectors) (all, t, alltime)  VL(i, t)
 # labor employment payment #;
(all, i, sectors) (all, t, alltime)  VK(i, t)
# physical capital rental payment #;
(all, i, sectors) (all, t, alltime)  VH(i, t)
 # knowledge capital rental payment #;
Read
VL from FILE BASEDATA HEADER "VL";
VK from FILE BASEDATA HEADER "VK";
VH from FILE BASEDATA HEADER "VH";

Variable
(all, i, sectors) (all, t, alltime)   lab(i, t)
 # labor employment #;
(all, t, alltime)                    wag(t)
# labor wage rate #;
(all, i, sectors) (all, t, alltime)  cap(i, t)
# physical capital stock #;
(all, i, sectors) (all, t, alltime)   prk(i, t)
# implicit rental price of physical stock #;
(all, i, sectors) (all, t, alltime)  hcp(i, t)
# knowledge capital stock #;
(all, i, sectors) (all, t, alltime)   phc(i, t)
# implicit rental price of knowledge stock #;

Update
(all, i, sectors) (all, t, alltime)   VL(i, t) = lab(i, t)*wag(t);
(all, i, sectors) (all, t, alltime)   VK(i, t) = cap(i, t)*prk(i, t);
(all, i, sectors) (all, t, alltime)   VH(i, t) = hcp(i, t)*phc(i, t);


!========================================
Import component of each Armington good
========================================!
Coefficient
   (all, j, goods) (all, t, alltime)   VM(j, t)
   # import component for each Armington good #;
Read
   VM from FILE BASEDATA HEADER "VM";
Variable
   (all, j, goods) (all, t, alltime)   imq(j, t)
     # quantity of import for each Armington good #;
   (all, j, goods) (all, t, alltime)   pmr(j, t)
     # price of import for each Armington good #;
Update
   (all, j,goods) (all, t, alltime)   VM(j, t) = imq(j, t)*pmr(j, t);

!================================================================
Producer problem characterization: demand for E commodity:
allocate aggregate E bundle into each E commodity
================================================================!
```

```
Coefficient
(parameter)(all, i, sectors)
SIGMA_1E(i)   # energy substitution elasticity#;
(all, j, goods_e) (all, t, alltime)
TCAR(j,t) # ad valorem equivalent carbon tax #;
(all, j, goods_e) (all, i, sectors) (all, t, alltime)
S_V1EE (j, i, t)   # cost share of individual E commodity in E bundle#;
(all, i, sectors) (all, t, alltime)
V1_E(i,t)    # value of energy bundle input #;

Read
SIGMA_1E from FILE BASEDATA header "S1E";
TCAR from File BASEDATA header  "TCAR";

Formula
(all, i, sectors) (all, t, alltime)
V1_E(i, t) = sum {j, goods_e, V1E(j, i, t)};
(all, j, goods_e) (all, i, sectors) (all, t, alltime)
S_V1EE(j, i, t) = V1E(j, i, t) / V1_E(i, t);
! S_V1EE represent the cost share of individual E commodity in E bundle,
 so double EE !
Variable
(CHANGE)    (all, j, goods_e) (all, t, alltime)
delTCAR(j,t)              # ad valorem equivalent carbon tax #;
(all, i, sectors) (all, t, alltime)  ent (i, t)
# quantity of energy bundle #;
(all, i, sectors) (all, t, alltime)  pre (i, t)
# price index of energy bundle #;
Update
(CHANGE)    (all, j, goods_e) (all, t, alltime)
TCAR(j,t) = delTCAR(j,t)  ;
Equation
E_en # producer demand for individual energy commodity #
(all, j, goods_e) (all, i, sectors) (all, t, alltime)
en(j,i,t) = SIGMA_1E(i)*[pre(i,t) - pry(j,t) - 100/(1+TCAR(j,t))*delTCAR(j,t)]
      + ent(i,t);

E_pre  # price index of energy bundle inputs in each sector #
(all, i, sectors) (all, t, alltime)
pre(i, t) = sum{j, goods_e,
         S_V1EE(j,i,t) * [pry(j,t) + 100/(1+TCAR(j,t))*delTCAR(j,t)]};

!======================================================================
Producer demand for individual material commodity:
allocate aggregate material bundle into individual M commodities
======================================================================!
Coefficient
(all, j, goods_m) (all, i, sectors) (all, t, alltime)  S_V1MM(j, i, t)
# cost share of individual material commodity in material bundle#;
(all, i, sectors) (all, t, alltime)  V1_M(i,t)
 # value of material bundle inputs #;
(parameter)  (all, i, sectors)   SIGMA_1M(i)
# material substitution elasticity #;
Read
SIGMA_1M from FILE BASEDATA header "S1M";

Formula
(all, i, sectors) (all, t, alltime)
V1_M(i, t) = sum { j, goods_m, V1M(j, i, t)};
(all, j, goods_m) (all, i, sectors) (all, t, alltime)
S_V1MM (j, i, t) = V1M(j, i, t) / V1_M(i, t);
Variable
(all, i, sectors) (all, t, alltime)  oin (i,t)
# quantity of material bundle inputs #;
(all, i, sectors) (all, t, alltime)  poi (i,t)
```

```
# price index of material bundle inputs #;

Equation
E_oi # producer demand for individual material commodity #
(all, j, goods_m) (all, i, sectors) (all, t, alltime)
oi(j, i, t) = SIGMA_1M(i) * [poi(i, t) - pry(j, t)] + oin(i, t);
!POI: price index of material bundle,
PRY: price of individual Armington material good!
E_poi # price index of material bundle inputs in each sector#
(all, i, sectors) (all, t, alltime)
poi(i, t) = sum { j, goods_m, S_V1MM(j, i, t) * pry(j,t)} ;
! cost minimization of material commodity subject to exogenous
aggregate of material bundle!
!=====================================================================
Producer demand for labor, energy bundle, material bundle
- allocating aggregate physical input bundle Z into L, E, M
=====================================================================!

Coefficient
(all, i, sectors) (all, t, alltime) V1ZK (i, t)
# value of K input into the production of sector i #;
(all, i, sectors) (all, t, alltime) V1ZL (i, t)
 # value of L input into the production of sector i #;
(all, i, sectors) (all, t, alltime) V1ZE (i, t)
# value of E input into the production of sector i #;
(all, i, sectors) (all, t, alltime) V1ZM (i, t)
 # value of M input into the production of sector i #;
(all, i, sectors) (all, t, alltime) V1_Z(i, t)
# value of tangible physical inputs into production #;
(all, i, sectors) (all, t, alltime) S_V1ZK (i, t)
# cost share of K in tangible physical bundle Z#;
(all, i, sectors) (all, t, alltime) S_V1ZL (i, t)
# cost share of L in tangible physical inputs Z #;
(all, i, sectors) (all, t, alltime) S_V1ZE (i, t)
# cost share of E in tangible physical bundle Z #;
(all, i, sectors) (all, t, alltime) S_V1ZM (i, t)
# cost share of M in tangible physical bundle Z #;
(parameter) (all, i, sectors) SIGMA_1Z(i)
 # KLEM substitution elasticity #;

Read
SIGMA_1Z from FILE BASEDATA Header "S1Z";
Formula
(all, i, sectors) (all, t, alltime)  V1ZK(i, t) = VK(i, t) ;
(all, i, sectors) (all, t, alltime)  V1ZL(i, t) = VL(i, t) ;
(all, i, sectors) (all, t, alltime)  V1ZE(i, t) = V1_E(i, t) ;
(all, i, sectors) (all, t, alltime)  V1ZM(i, t) = V1_M(i, t) ;
(all, i, sectors) (all, t, alltime)
V1_Z(i, t) = V1ZK(i, t) + V1ZL(i, t) + V1ZE(i, t) + V1ZM(i, t);
(all, i, sectors) (all, t, alltime)  S_V1ZK(i, t) = V1ZK(i, t) / V1_Z(i, t);
(all, i, sectors) (all, t, alltime)  S_V1ZL(i, t) = V1ZL(i, t) / V1_Z(i, t);
(all, i, sectors) (all, t, alltime)  S_V1ZE(i, t) = V1ZE(i, t) / V1_Z(i, t);
(all, i, sectors) (all, t, alltime)  S_V1ZM(i, t) = V1ZM(i, t) / V1_Z(i, t);

Variable
(all, i, sectors) (all, t, alltime) ouz (i, t)
# quantity of tangible physical inputs composite #;
(all, i, sectors) (all, t, alltime) prz (i, t)
# price index of tangible physical input composite #;

Equation
E_lab # producer demand for labor #
(all, i, sectors) (all, t, alltime)
lab(i, t) = SIGMA_1Z(i) * [prz(i,t) - wag(t)] + ouz(i,t) ;

E_ent # producer demand for energy bundle #
(all, i, sectors) (all, t, alltime)
ent(i, t) = SIGMA_1Z(i) * [prz(i,t) - pre(i,t)] + ouz(i,t) ;

E_oin # producer demand for material bundle #
(all, i, sectors) (all, t, alltime)
```

```
oin(i, t) = SIGMA_1Z(i) * [prz(i,t) - poi(i, t)] + ouz(i,t) ;

E_prz  # price index of physical inputs bundle Z #
(all, i, sectors) (all, t, alltime)
prz(i, t) = S_V1ZL(i, t) * wag(t) + S_V1ZK( i, t) * prk(i, t)
+ S_V1ZE(i, t) * pre(i, t) + S_V1ZM(i, t) * poi(i, t);
!========================================================
Producer demand for tangible physical input bundle Z
========================================================!
Coefficient
(all, i, sectors) (all, t, alltime)  V1QZ(i, t)
# value of tangible physical input Z used in sector i #;
(all, i, sectors) (all, t, alltime) V1QH(i, t)
# value of knowledge input H used in sector i #;
(all, i, sectors) (all, t, alltime)  V1_Q(i, t)
# value of domestic output of sector i #;
(all, i, sectors) (all, t, alltime)  S_V1QZ(i, t)
# cost share of Z in domestic output of sector i #;
(all, i, sectors) (all, t, alltime)  S_V1QH(i, t)
# cost share of H in domestic output of sector i #;
(parameter) (all, i, sectors)     SIGMA_1Q(i)
# substitution elasticity between tangible / intangible input #;

Read
SIGMA_1Q from FILE BASEDATA Header "S1Q";
Formula
(all, i, sectors) (all, t, alltime)  V1QZ(i, t) = V1_Z(i, t);
(all, i, sectors) (all, t, alltime)  V1QH(i, t) = VH(i, t) ;
(all, i, sectors) (all, t, alltime)  V1_Q (i, t) = V1QZ(i, t) + V1QH(i, t);
(all, i, sectors) (all, t, alltime)   S_V1QZ (i, t) = V1QZ(i, t) / V1_Q(i, t);
(all, i, sectors) (all, t, alltime)   S_V1QH (i, t) = V1QH(i, t) / V1_Q(i, t);

Variable
  (all, i, sectors) (all, t, alltime)  oup (i, t)
# quantity of domestic production output of sector i #;
  (all, i, sectors) (all, t, alltime)  prp (i, t)
# producer price index of sector i #;

Equation
E_ouz   # producer demand for tangible physical inputs Z#
(all, i, sectors) (all, t, alltime)
ouz(i,t) =  SIGMA_1Q(i) * [prp(i, t) - prz(i, t)] + oup(i, t);
!PRP: producer price, PRZ: price index of tangible physical inputs composite !

E_prp  # producer price index of sector i #
(all, i, sectors) (all, t, alltime)
prp(i, t) = S_V1QZ(i, t) * prz(i, t) + S_V1QH(i, t) * phc(i, t);
! cost minimization of Z-H input subject to exogenous domestic
production output OUP.!

E_phc # implicit rental price of knowledge capital stock PHC#
(all, i, sectors) (all, t, alltime)
phc(i, t) = prp(i, t) + 1/SIGMA_1Q(i)*oup(i,t) - 1/SIGMA_1Q(i) * hcp(i,t) ;
! PHC: the value of marginal product of knowledge stock at top tier production!

E_prk  # implicit rental price of physical capital PRK#
(all, i, sectors) (all, t, alltime)
prk(i,t) = prp(i,t) + 1/SIGMA_1Z(i)*ouz(i,t) - 1/SIGMA_1Z(i)*cap(i, t)
        + 1/SIGMA_1Q(i)*oup(i,t) +  1/SIGMA_1Q(i)*ouz(i,t) ;
! PRK: the value of marginal product of physical capital stock
 in producing physical inputs bundle!
!==================================================================
One-to-one correspondence between commodity and sector:
OUP determined by OUG, PRD determined by PRP
==================================================================!
Mapping GOD2SEC from goods to sectors;
Formula (all, j, goods)  GOD2SEC(j) = $POS(j);
Mapping SEC2GOD from sectors to goods;
Formula  (all, i, sectors)   SEC2GOD(i) = $POS(i);
!the integer function $POS: identity the position number
 of element name in the defined set!
```

```
Coefficient
(all, j, goods) (all, t, alltime)    S_V1YQ (j, t)
# share of domestically-produced component Q of Armington good j #;
(all, j, goods) (all, t, alltime)    S_V1YM (j, t)
# share of imported component M of Armington good j #;
(all, j, goods) (all, t, alltime )    V1YQ(j, t)
# value of domestically-produced component Q of Armington good j #;
(all, j, goods) (all, t, alltime )    V1YM(j, t)
# value of imported component M of Armington good j #;
(all, j, goods) (all, t, alltime )    V1_Y(j, t)
# value of Armington good j #;
(parameter)  (all, j, goods)       SIGMA_1DF (j)
# substitution elast. between domestically-produced/imported components#;

Read
SIGMA_1DF from FILE Basedata Header "S1DF";
Formula
(all, j, goods) (all, t, alltime)    V1YQ(j, t) = V1_Q(GOD2SEC(j),t);
(all, j, goods) (all, t, alltime)    V1YM(j, t) = VM(j, t);
(all, j, goods) (all, t, alltime )   V1_Y(j, t) = V1YQ(j, t) + V1YM(j, t);
(all, j, goods) (all, t, alltime)    S_V1YQ (j, t) = V1YQ(j, t) / V1_Y(j, t) ;
(all, j, goods) (all, t, alltime)    S_V1YM (j, t) = V1YM(j, t) / V1_Y(j, t) ;
Variable
(all, j, goods) (all, t, alltime)   oug (j, t)
# quantity of domestically-produced components of the Armington good j #;
(all, j, goods) (all, t, alltime)   prd (j, t)
# price of domestically-produced components of the Armington good j #;
(all, j, goods) (all, t, alltime)   ouy (j, t)
 # quantity of Armington good j #;
Equation
E_oup    # mapping sector output to corresponding good #
(all, i, sectors) (all, t, alltime)   oup (i, t) = oug (SEC2GOD(i), t);

E_oug    # domestically-produced component of the Armington good#
(all, j, goods) (all, t, alltime)
oug (j, t) = ouy(j, t) + SIGMA_1DF(j)* [pry(j, t) - prd(j, t)] ;

E_imq     # import component of the Armington good#
(all, j, goods) (all, t, alltime)
imq (j,t) = ouy (j, t) + SIGMA_1DF (j)* [pry(j, t) - pmr(j, t)] ;

E_prd    #price of domestically-produced component of the Armington good#
(all, j, goods) (all, t, alltime)   prd(j, t) = prp (GOD2SEC(j), t);

E_pry   # price of Armington good #
(all, j, goods) (all, t, alltime)
pry(j, t) = S_V1YQ (j, t) * prd (j, t) + S_V1YM (j, t) * pmr (j,t) ;
!=====================================================
Intertemporal set
=====================================================!
Coefficient(parameter) (all, t, alltime) year(t);
READ year FROM FILE basedata Header "YEAR";
Coefficient (all, t, fwdtime) dt(t) ;
FORMULA (all, t, fwdtime) dt(t) = year(t+1) - year(t) ;


!======================================================
Investment and physical capital accumulation
=====================================================!
Coefficient
(parameter)                          DELTA
# depreciation rate of physical capital stock #;
(parameter)                          LABGROW
# effective labor growth rate #;
(parameter)                          PHI
# investment adjustment cost coefficient #;
(all, t, alltime)                    TCOR(t)
# corporate income tax rate #;
(all, t, alltime)                    TITC(t)
```

```
# investment tax credit #;
(all, i, sectors) (all, t, alltime)    LCAP(i,t)
# physical capital stock #;
(all, i, sectors) (all, t, alltime)    LJNV(i,t)
# installed investment in physical capital #;
(all, i, sectors) (all, t, alltime)    LINV(i,t)
# raw investment good (adjustment cost included)#;
(all, i, sectors) (all, t, alltime)    LLAM(i,t)
# shadow price of physical capital#;
(all, i, sectors) (all, t, alltime)    LPRK(i,t)
#implicit rental price of physical capital #;
(all, t, alltime)                     LPRII(t)
#purchase price of raw investment good #;
(all, i, sectors) (all, t, alltime)   LTOB(i,t)
# Tobin's-q in physical capital investment #;

Read
DELTA from file BASEDATA header "DELT";
LABGROW from file BASEDATA header "LGOW";
PHI from file BASEDATA header "PHI";
TCOR from file BASEDATA header "TCOR";
TITC from file BASEDATA header "TITC";
LCAP from file BASEDATA header "CAP";
LJNV from file BASEDATA header "JNV";
LPRII from file BASEDATA header "PRII";
Variable
(CHANGE) (all, t, alltime)            delTCOR(t)
# corporate income tax rate #;
(CHANGE) (all, t, alltime)            delTITC(t)
# rate of investment tax credit #;
(all, i, sectors) (all, t, alltime)    jnv(i, t)
# installed investment in physical capital #;
(all, i, sectors) (all, t, alltime)    inv(i, t)
# raw investment good (adjustment cost included) #;
(all, t, alltime)                     prii(t)
#purchase price of raw investment good #;
(all, i, sectors) (all, t, alltime)    lam(i, t)
# shadow price of physical capital #;
(all, i, sectors) (all, t, alltime)    tob(i, t)
# Tobin's-q in physical capital investment #;

Update
(CHANGE)  (all, t, alltime)          TCOR(t) = delTCOR(t);
(CHANGE)  (all, t, alltime)          TITC(t) = delTITC(t);
(all, i, sectors) (all, t, alltime) LCAP(i,t) = cap(i,t) ;
(all, i, sectors) (all, t, alltime) LJNV(i,t) = jnv(i,t) ;
(all, t, alltime)                  LPRII(t) = prii(t);
Formula
(all, i, sectors) (all, t, alltime)
LLAM(i,t) = [1-TITC(t)] * LPRII(t) * [1 + PHI * LJNV(i,t) / LCAP(i,t)];
(all, i, sectors) (all, t, alltime)
LTOB(i,t) = LLAM(i, t) / [(1-TITC(t)) * LPRII(t)];
(all, i, sectors)(all, t, alltime)
LPRK(i,t) = VK(i,t) / LCAP(i,t);
!======================================
Producer demand for investment good
======================================!

Equation
E_tob  # Tobin's-q as a function of shadow price of physical capital #
(all, i, sectors) (all, t, alltime)
tob(i,t) = lam(i,t) - prii(t) + 100/(1-TITC(t)) * delTITC(t) ;

E_jnv  # demand for installed investment #
(all, i, sectors) (all, t, alltime)
jnv(i, t) = [LTOB(i, t)/(LTOB(i,t)-1)] * tob(i, t) + cap (i, t);

E_inv  # demand for raw investment good including adjustment cost#
```

```
(all, i, sectors) (all, t, alltime)
inv(i,t) = [PHI*LJNV(i,t)/(PHI*LJNV(i,t)+2*LCAP(i,t))]
        * [jnv(i,t)-cap(i,t)] + jnv(i,t);
!==========================================
Law of motion for physical capital stock
==========================================!
Coefficient
(all, i, sectors)(all, t, fwdtime)  S_K1(i, t);

Formula
(all, i, sectors)(all, t, fwdtime)
S_K1(i, t)= LCAP(i, t) * [1- (DELTA+LABGROW) * dt(t)] / LCAP(i, t+1);
Equation
E_cap # percentage change of the law of motion for physical capital #
(all, i, sectors) (all, t, fwdtime)
cap(i, t+1) = S_K1(i, t) * cap(i, t) + (1-S_K1(i, t)) * jnv(i,t);
!========================================================
Law of motion for the shadow price of physical capital
========================================================!
Coefficient
(parameter) INTR  # interest rate #;
(all, i, sectors)(all, t, fwdtime)   S_K2(i, t)
# coefficient used in equation #;
(all, i, sectors)(all, t, alltime)   S_K3(i, t)
# coefficient used in equation #;
Read
INTR from file Basedata header "INTR";
Formula
(all, i, sectors)(all, t, fwdtime)
S_K2(i, t) = [1+ (INTR+DELTA)*dt(t)] * LLAM(i, t) / LLAM(i, t+1);
(all, i, sectors)(all, t, alltime)
S_K3(i, t) = (1-TCOR(t)) * LPRK(i, t)
/[(1-TCOR(t))*LPRK(i,t)
+ (1-TITC(t))*LPRII(t)*(PHI/2)*(LJNV(i,t)/LCAP(i,t))^2] ;
Equation
E_lam  # law of motion for shadow price of physical capital #
(all, i, sectors) (all, t, fwdtime)
lam(i, t+1) = S_K2(i, t) * lam(i, t)
+ [1-S_K2(i,t)] * S_K3(i,t) * [prk(i, t) - 100 /(1-TCOR(t)) * delTCOR(t) ]
+ [1-S_K2(i,t)] * [1 - S_K3(i,t)]
* [prii(t) + 2 * (inv(i,t)-cap(i,t)) - 100/(1-TITC(t))*delTITC(t)]  ;
Equation
E_lamend  # boundary condtion for shadow price of physical capital #
(all, i, sectors) (all, t, endtime)
lam(i, t) =  S_K3(i,t) * [prk(i, t) - 100 /(1-TCOR(t)) * delTCOR(t)]
+[1 - S_K3(i,t)]
* [prii(t) + 2*(inv(i,t)-cap(i,t)) - 100/(1-TITC(t))*delTITC(t)];
!=======================================================
R&D and knowledge capital accumulation
=======================================================!
Coefficient
(parameter)                               AH
# knowledge creation efficiency #;
(parameter)                               ALPHA
# power on R in IPF #;
(parameter)                               BETA
# power on H in IPF #;
(parameter)                               DELTAH
# depreciation rate of knowledge capital #;
(all, t, alltime)                          TRTC(t)
# R&D tax credit #;
```

```
(all, i, sectors) (all, t, alltime)        LRNV(i,t)
# R&D investment #;
(all, t, alltime)                         LPRRR(t)
# price of raw R&D good #;
(all, i, sectors) (all, t, alltime)        LHCP(i,t)
# knowledge capital stock #;
(all, i, sectors) (all, t, alltime)        LLAMR(i,t)
# shadow price of knowledge capital#;
(all, i, sectors) (all, t, alltime)        LPHC(i,t)
# implicit rental price of knowledge capital #;
Read
AH  from file BASEDATA header "AH";
ALPHA  from file BASEDATA header "ALPH";
BETA  from file BASEDATA header "BETA";
DELTAH  from file BASEDATA header "DETH";
TRTC  from file BASEDATA header "TRTC";
LHCP  from file BASEDATA header "HCP";
LRNV  from file BASEDATA header "RNV";
LPRRR  from file BASEDATA header "PRRR";

Formula
(all, i, sectors) (all, t, alltime)
LPHC(i,t) = VH(i,t)/LHCP(i,t);
(all, i, sectors) (all, t, alltime)
LLAMR(i,t) =(1-TRTC(t)) * LPRRR(t)
/ [AH*ALPHA*[LRNV(i,t)^(ALPHA-1)]*(LHCP(i,t)^BETA)];

VARIABLE
(CHANGE) (all, t, alltime)                delTRTC(t)
 # ordinary change of R&D tax credit #;
(all, i, sectors) (all, t, alltime)       rnv(i,t)
# R&D investment in knowledge capital #;
(all, t, alltime)                         prrr(t)
# purchase price of raw R&D good #;
(all, i, sectors) (all, t, alltime)       lamr(i,t)
# shadow price of knowledge capital#;
(all, i, sectors) (all, t, alltime)       tobr(i,t)
# Tobin's-q for R&D investment #;
Update
(CHANGE)  (all, t, alltime)               TRTC(t) = delTRTC(t);
(all, i, sectors) (all, t, alltime)       LHCP(i,t) = hcp(i,t);
(all, i, sectors) (all, t, alltime)       LRNV(i,t) = rnv(i,t);
(all, t, alltime)                        LPRRR(t) = prrr(t);

!=====================================================
producer demand for R&D investment
=====================================================!
Equation
E_tobr # Tobin's-q for R&D investment #
(all, i, sectors) (all, t, alltime)
tobr(i,t) = lamr(i,t) - prrr(t) + 100 /(1-TRTC(t)) * delTRTC(t);
E_rnv  # R&D investment #
(all, i, sectors) (all, t, alltime)
0 = tobr(i,t) + (ALPHA-1) * rnv(i,t) + BETA * hcp(i,t);
!=====================================================
Law of motion for knowledge capital stock
=====================================================!
Coefficient
(all, i, sectors) (all, t, fwdtime)  S_H1(i,t);
Formula
(all, i, sectors) (all, t, fwdtime)
S_H1(i,t)=  [1-(DELTAH+LABGROW)*dt(t)] * LHCP(i,t)/LHCP(i,t+1);
Equation
E_hcp  # Law of motion for knowledge capital stock #
(all, i, sectors) (all, t, fwdtime)
```

```
hcp(i,t+1) = S_H1(i,t) * hcp(i,t)
             + [1-S_H1(i,t)] * [ALPHA*rnv(i,t) + BETA*hcp(i,t)];

!====================================================
Law of motion for shadow price of knowledge capital
====================================================!
Coefficient
(all, i, sectors) (all, t, fwdtime)        S_H2(i,t);
(all, i, sectors) (all, t, alltime)        S_H3(i,t);
(all, i, sectors) (all, t, endtime)        S_H4(i,t);

Formula
(all, i, sectors) (all, t, fwdtime)
S_H2(i,t) = [1 + dt(t)*(INTR + DELTAH) - dt(t)*AH*BETA
          * (LRNV(i,t)^ALPHA)*(LHCP(i,t)^(BETA-1))]
          * LLAMR(i,t) / LLAMR(i,t+1);

(all, i, sectors) (all, t, fwdtime)
S_H3(i,t) = [- dt(t)*AH*BETA*(LRNV(i,t)^ALPHA)
          *(LHCP(i,t)^(BETA-1))]
          / [1 + dt(t)*(INTR+DELTAH) - dt(t)*AH*BETA
          * (LRNV(i,t)^ALPHA)*(LHCP(i,t)^(BETA-1))];

(all, i, sectors) (all, t, endtime)
S_H4(i,t) = [- AH*BETA*(LRNV(i,t)^ALPHA)
          *(LHCP(i,t)^(BETA-1))]
          / [INTR + DELTAH - AH*BETA*(LRNV(i,t)^ALPHA)
          *(LHCP(i,t)^(BETA-1))];
Equation
E_lamr  # Law of motion for the shadow price of knowledge capital stock #
(all, i, sectors) (all, t, fwdtime)
lamr(i,t+1) = S_H2(i,t) * [lamr(i,t) +
              S_H3(i,t)*(ALPHA*rnv(i,t)+(BETA-1)*hcp(i,t))]
              +(1-S_H2(i,t))*[phc(i,t) - 100/(1-TCOR(t))* delTCOR(t)];

E_lamrend  # boundary condtion for shadow price of knowledge capital #
(all, i, sectors) (all, t, endtime)
S_H4(i,t) * [ALPHA*rnv(i,t)+(BETA-1)*hcp(i,t)] + lamr(i,t)
= phc(i,t) - 100/(1-TCOR(t))* delTCOR(t) ;

!============================================================
Characterization of consumption for the representative household
============================================================!

!=============================
HH after-tax current income
=============================!
Coefficient
(all, t, alltime)                   LINCM(t)
# after-tax income #;
(all, t, alltime)                   TINC(t)
# income tax rate #;
(all, t, alltime)                   V_L(t)
# value of aggregate labor income payment #;
(all, i, sectors) (all, t, alltime)    S_VL(i, t)
# share of each sector's labor income payment #;

Read
TINC from file basedata header "TINC";

Variable
(CHANGE) (all, t, alltime)           delTINC(t)
# ordinary change in income tax rate #;
(all, t, alltime)                   incm(t)
# after-tax current income #;

Update
(CHANGE) (all, t, alltime)  TINC(t) = delTINC(t) ;

Formula
(all, t, alltime) V_L(t) = sum {i, sectors, VL(i, t)} ;
```

```
(all, t, alltime)   LINCM(t) = [1-TINC(t)] * V_L(t) ;
(all, i, sectors) (all, t, alltime)  S_VL(i, t) = VL(i, t) / V_L(t);

Equation
E_incm   # HH after-tax current income #
(all, t, alltime)
incm(t) = - 100 /(1-TINC(t)) * delTINC(t)
       + wag(t)
       + sum{i, sectors, S_VL(i, t)*lab(i, t)} ;

!============================================
HH total wealth (financial plus human wealth)
============================================!
!================
Financial wealth
================!
Coefficient
(parameter)                         FORE_C
# share of consumption driven by perfect foresight #;
(parameter)                         TIMEPREF
# pure rate of time preference #;
(parameter)                         MPC
# marginal propensity to consume #;
(all, t, alltime)                   V2(t)
# HH aggregate consumption expenditure #;
(all, i, sectors) (all, t, alltime)     LSTM(i, t)
# sector-specific equity value in stock market #;
(all, t, alltime)                   LSTMT(t)
# economy-wide equity value in stock market #;
(all, t, alltime)                   LWELA(t)
# financial wealth component in HH total wealth #;
(all, t, alltime)                   LWELT(t)
# HH total wealth #;
(all, t, alltime)                   S_C2(t)
# coefficient used in equation E_welt #;
(all, i, sectors)(all, t, alltime)      S_C3(i,t)
# coefficient used in equation E_wela #;
Read
FORE_C from file Basedata header "FORE";
TIMEPREF from file Basedata header "TIMP";
MPC from file Basedata header "MPC";
Formula
(all, i, sectors) (all, t, alltime)
LSTM(i,t) = LLAM(i,t)*LCAP(i,t) + LLAMR(i,t)*LHCP(i,t);
!equity value from both physical and knowledge capital stock!
(all, t, alltime)
LSTMT(t) = sum{i, sectors, LSTM(i, t)};
(all, t, alltime)
LWELA(t) = LSTMT(t);
(all, t, alltime)
V2(t) = sum{ j, goods_e, V2E(j, t)} + sum{ j, goods_m, V2M(j, t)};
(all, t, alltime)
LWELT(t) = [V2(t) - (1-FORE_C) * MPC * LINCM(t)] / (FORE_C * TIMEPREF);
(all, t, alltime)    S_C2(t) = LWELA(t) / LWELT(t) ;
(all, i, sectors)(all, t, alltime)  S_C3(i,t) = LSTM(i,t) / LSTMT(t);
Variable
(all, i, sectors) (all, t, alltime)     stm(i, t)
 # equity value of sector i in stock market #;
(all, t, alltime)                   wela(t)
 # financial wealth component in HH total wealth #;
(all, t, alltime)                   welh(t)
 # huamn wealth component in HH total wealth #;
(all, t, alltime)                   welt(t)
 # HH total wealth #;

Equation
E_welt   # HH total wealth as summation of financial and human wealth #
(all,t,alltime)  welt(t) = S_C2(t)*wela(t) + (1-S_C2(t))*welh(t);
```

```
E_wela   # financial wealth: holding of the equity value of firms #
(all,t,alltime)  wela(t) = sum{i, sectors, S_C3(i,t)*stm(i,t)};

E_stm    # equity value of firms #
(all,i,sectors) (all,t,alltime)
stm(i,t) = LLAM(i,t)*LCAP(i,t)/LSTM(i,t)*[lam(i,t) + cap(i,t)]
        + [1-LLAM(i,t)*LCAP(i,t)/LSTM(i,t)]*[lamr(i,t) + hcp(i,t)];
!==================
human wealth
==================!
Coefficient
(all, t, alltime)       LWELH(t)    # human wealth #;
(all, t, fwdtime)       S_C4(t)   # coefficient used E_welh #;
Formula
(all, t, alltime) LWELH(t) = LWELT(t) - LWELA(t);
(all, t, fwdtime) S_C4(t) = [1+(INTR-LABGROW)*dt(t)]*LWELH(t)/ LWELH(t+1);

Equation
E_welh      # Law of motion for the human wealth #
(all, t, fwdtime)
welh(t+1) = S_C4(t) * welh(t)
          + [1- S_C4(t)] * wag(t)
          + [1- S_C4(t)] * sum{i, sectors, S_VL(i,t) * lab(i,t)};
Equation
E_welhend  # boundary condtion for human wealth #
(all, t, endtime)
welh(t) = wag(t) + sum{i, sectors, S_VL(i,t)*lab(i,t)};

!======================
Aggregate consumption
======================!

Coefficient
(all, t, alltime)  S_C1(t)   # coefficient used in equation E_conp #;
Formula
(all, t, alltime)   S_C1(t) = (1-FORE_C) * MPC * LINCM(t) / V2(t) ;
Variable
(all, t, alltime)  conp(t)   # HH aggregate consumption #;
(all, t, alltime)  prct(t)    # consumer price index #;

Equation
E_conp   # aggregate consumption #
(all, t, alltime)
conp(t) = S_C1(t) * incm(t) + (1-S_C1(t)) * welt(t) - prct (t) ;

!=================================================================
allocating aggregate consumption CONP into energy & material bundle
=================================================================!
Coefficient
(all, t, alltime)                          S_V2E (t)
 # cost share of energy bundle in consumption expenditure #;
(all, t, alltime)                          S_V2M (t)
# cost share of material bundle in consumption expenditure #;
(all, t, alltime)                          V2_E (t)
 # value of HH expenditure on energy bundle #;
(all, t, alltime)                          V2_M (t)
# value of HH expenditure on material bundle #;
(parameter)                               SIGMA_20
# elasticity of E&M bundle substitution on top tier #;

Read
SIGMA_20 from file Basedata Header "S20";

Formula
```

```
(all, t, alltime)  V2_E(t) = sum{ j, goods_e, V2E(j, t)};
(all, t, alltime)  V2_M(t) = sum{ j, goods_m, V2M(j, t)};
(all, t, alltime)  S_V2E(t) = V2_E(t)/V2(t);
(all, t, alltime)  S_V2M(t) = V2_M(t)/V2(t);

Variable
(all, t, alltime)   cnpe(t)   # quantity of energy bundle consumed #;
(all, t, alltime)   prce(t)   # price of energy bundle consumed #;
(all, t, alltime)   cnpo(t)   # quantity of material bundle consumed #;
(all, t, alltime)   prco(t)   # price of material bundle consumed #;

Equation
E_cnpe  # HH demand for energy bundle #
(all, t, alltime)     cnpe(t) = conp(t) + SIGMA_2O * [prct(t) - prce(t)] ;

E_cnpo  # HH demand for material bundle #
(all, t, alltime)     cnpo(t) = conp(t) + SIGMA_2O * [prct(t) - prco(t)] ;

E_prct   # consumer price index #
(all, t, alltime)     prct(t) = S_V2E(t) * prce(t) + S_V2M(t) * prco(t) ;

!==============================================================
allocating energy bundle CNPE into individual energy commodities
==============================================================!
Coefficient
(parameter)                              SIGMA_2E
# elasticity of E commodity substitution in E bundle #;
(all, j, goods_e) (all, t, alltime)         S_V2EE(j, t)
 # cost share of E commodity in E bundle #;

Read
SIGMA_2E from file Basedata header "S2E";
Formula
(all, j, goods_e) (all, t, alltime) S_V2EE(j, t) = V2E(j,t) / V2_E(t) ;

Equation
E_cone  # individual energy commodity consumed by HH #
(all, j, goods_e) (all, t, alltime)
cone(j,t) = cnpe (t) + SIGMA_2E * [prce(t) - pry(j,t)
       - 100/(1+TCAR(j,t))*delTCAR(j,t)];
E_prce  # price index of energy bundle in consumption #
(all, t, alltime)
prce(t) = sum{j, goods_e,
         S_V2EE(j,t)* [pry(j,t) + 100/(1+TCAR(j,t))*delTCAR(j,t)]} ;

!==================================================================
allocating material bundle CNPO into individual material commodities
==================================================================!
Coefficient
(parameter) SIGMA_2M  # elasticity of M commodity substitution in M bundle #;
(all, j, goods_m) (all, t, alltime)  S_V2MM(j, t)
# cost share of each individual material commodity in material bundle #;

Read
SIGMA_2M from file Basedata Header "S2M";
Formula
(all, j, goods_m) (all, t, alltime)  S_V2MM(j, t) = V2M(j, t) / V2_M(t) ;

Equation
E_cono  # individual material commodity consumed by HH #
(all, j, goods_m) (all, t, alltime)
cono(j, t) = cnpo (t) + SIGMA_2M*[prco(t) - pry (j,t)] ;

E_prco  # price index of material bundle in consumption #
(all, t, alltime)  prco(t) = sum{j, goods_m, S_V2MM(j,t)* pry(j,t)} ;

!=================================================
```

```
Characterization of investment sector
====================================================!
!==================================
demand for individual E commodity
=================================!

Coefficient
(all, t, alltime)  V3_E(t)
# value of energy bundle in investment sector#;
(all, j, goods_e) (all, t, alltime) S_V3EE(j, t)
# cost share of E commodity in E bundle #;
(parameter) SIGMA_3E
# energy commodity substitution elasticity in investment sector #;

Read
SIGMA_3E from file Basedata header "S3E";
Formula
(all, t, alltime)  V3_E(t) = sum{j, goods_e, V3E(j, t)};
(all, j, goods_e) (all, t, alltime)   S_V3EE(j, t) = V3E(j, t)/ V3_E(t);

Variable
(all, t, alltime)    iite(t)
 # demand for energy bundle in investment sector #;
(all, t, alltime)    prie(t)
# price of energy bundle in investment sector #;

Equation
E_iine  # investment sector demand for individual energy commodity #
(all, j, goods_e) (all, t, alltime)
iine(j,t) = SIGMA_3E*[prie(t) - pry(j,t) - 100/(1+TCAR(j,t))*delTCAR(j,t)]
        + iite(t);
E_prie  # price index of energy bundle in investment sector #
(all, t, alltime)
prie(t) = sum{j, goods_e, S_V3EE(j,t)
          * [pry(j,t) + 100/(1+TCAR(j,t))*delTCAR(j,t)]} ;
!===================================
demand for individual M commodity
===================================!
Coefficient
(all, t, alltime)                    V3_M(t)
#value of material bundle in investment sector#;
(all, j, goods_m) (all, t, alltime)      S_V3MM(j, t)
 #cost share of M commodity in M bundle #;
(parameter)                         SIGMA_3M
# M commodity substitution elasticity in investment sector #;
Read
SIGMA_3M from file Basedata header "S3M";

Formula
(all, t, alltime)  V3_M(t)= sum{j, goods_m, V3M(j,t)};
(all, j, goods_m) (all, t, alltime)  S_V3MM(j, t) = V3M(j, t)/ V3_M(t);

Variable
(all, t, alltime)                   iito(t)
# demand for material bundle in investment sector #;
(all, t, alltime)                   proi(t)
# price of material bundle in investment sector #;
Equation
E_iino     # investment sector demand for individual material commodity #
(all, j, goods_m) (all, t, alltime)
iino(j, t) = SIGMA_3M * [proi(t) - pry(j,t)] + iito(t) ;

E_proi     # price index of material bundle in investment sector #
(all, t, alltime)
proi(t) = sum{j, goods_m, S_V3MM(j, t) * pry(j,t)} ;

!=================================
Demand for energy/material bundle
=================================!
```

```
Coefficient
(all, t, alltime)                               V3(t)
# value of all commodity inputs into investment sector#;
(all, t, alltime)                               S_V3E(t)
# cost share of energy bundle #;
(all, t, alltime)                               S_V3M(t)
# cost share of material bundle #;
(parameter)                                     SIGMA_3O
# E/M substitution elasticity in investment sector #;

Read
SIGMA_3O from file Basedata header "S3O";

Formula
(all, t, alltime)               V3(t) = V3_E(t) + V3_M(t);
(all, t, alltime)               S_V3E(t) = V3_E(t)/ V3(t);
(all, t, alltime)               S_V3M(t) = V3_M(t)/ V3(t);

Variable
(all, t, alltime)   invt(t)  # supply of raw investment good #;

Equation
E_iite   # investment sector demand for energy bundle #
(all, t, alltime)
iite(t) = SIGMA_3O * [prii(t) - prie(t)] + invt(t) ;

E_iito   # investment sector demand for material bundle #
(all, t, alltime)
iito(t) = SIGMA_3O * [prii(t) - proi(t)] + invt(t) ;

E_prii   # purchase price of raw investment good #
(all, t, alltime)
prii(t) = S_V3E(t) * prie(t) + S_V3M(t) *proi(t);

!===============================================================
Characterization of R&D sector
===============================================================!
!================================
demand for individual E commodity
================================!

Coefficient
(all, t, alltime)                         V4_E(t)
# value of energy bundle in R&D sector#;
(all, j, goods_e) (all, t, alltime)       S_V4EE(j, t)
# cost share of E commodity in E bundle #;
(parameter)                               SIGMA_4E
# energy commodity substitution elasticity in R&D sector #;

Read
SIGMA_4E from file Basedata header "S4E";

Formula
(all, t, alltime)                      V4_E(t) = sum{ j, goods_e, V4E(j,t)};
(all, j, goods_e) (all, t, alltime)    S_V4EE(j, t) = V4E(j, t)/ V4_E(t);

Variable
(all, t, alltime)                         rrte(t)
# demand for E bundle in R&D sector #;
(all, t, alltime)                         prre(t)
# price of E bundle in R&D sector #;

Equation
E_rrne     # R&D sector demand for individual E commodity #
(all, j, goods_e) (all, t, alltime)
rrne(j,t) = SIGMA_4E * [prre(t) - pry(j,t) - 100/(1+TCAR(j,t))*delTCAR(j,t)]
          + rrte(t) ;

E_prre     # price index of E bundle in R&D sector #
(all, t, alltime)
prre(t) = sum{j, goods_e, S_V4EE(j,t) * [pry(j,t)
       + 100/(1+TCAR(j,t))*delTCAR(j,t)]} ;
```

```
!=====================================================
demand for individual material commodity
=====================================================!

Coefficient
    (all, t, alltime)                       V4_M(t)
    #value of material bundle in R&Dsector#;
    (all, j, goods_m) (all, t, alltime)         S_V4MM(j, t)
    # cost share of M commodity in M bundle #;
    (parameter)                             SIGMA_4M
    # material commodity substitution elasticity in R&Dt sector #;

Read
    SIGMA_4M from file Basedata header "S4M";

Formula
    (all, t, alltime)  V4_M(t) = sum{j, goods_m, V4M(j, t)};
    (all, j, goods_m) (all, t, alltime)   S_V4MM(j,t) = V4M(j,t)/ V4_M(t);
Variable
    (all, t, alltime)    rrto(t)
    # demand for material bundle in R&D sector #;
    (all, t, alltime)    prro(t)
    # price of material bundle in R&D sector #;
Equation
E_rrno      # R&D sector demand for individual material commodity #
    (all, j, goods_m) (all, t, alltime)
    rrno(j, t) = SIGMA_4M*[prro(t)-pry(j,t)] + rrto(t) ;
E_prro      # price index of material bundle in R&D sector #
    (all, t, alltime)
    prro(t) = sum{j, goods_m, S_V4MM(j,t)*pry(j,t)} ;

!=====================================================
Demand for energy/material bundle of R&D sector
=====================================================!

Coefficient
    (all, t, alltime)  V4(t)
     # value of all commodity inputs into R&D sector#;
    (all, t, alltime)   S_V4E(t)
    # cost share of energy bundle #;
    (all, t, alltime)   S_V4M(t)
    # cost share of material bundle #;
    (parameter) SIGMA_4O
    # E/M substitution elasticity in investment sector #;
Read
    SIGMA_4O from file Basedata header "S4O";
Formula
    (all, t, alltime)    V4(t) = V4_E(t) + V4_M(t);
    (all, t, alltime)    S_V4E(t) = V4_E(t)/ V4(t);
    (all, t, alltime)    S_V4M(t) = V4_M(t)/ V4(t);
Variable
    (all, t, alltime)     rnvt(t)    # total supply of raw R&D good #;
Equation
E_rrte        # R&D sector demand for energy bundle #
    (all, t, alltime)
    rrte(t) = SIGMA_4O * [prrr(t) - prre(t)] + rnvt(t) ;
E_rrto        # R&D sector demand for material bundle #
    (all, t, alltime)
    rrto(t) = SIGMA_4O * [prrr(t) - prro(t)] + rnvt(t) ;
E_prrr        # purchase price of raw investment good #
    (all, t, alltime)
    prrr(t) = S_V4E(t) * prre(t) + S_V4M(t) *prro(t);

!======================================
Government behavior
```

```
=========================================!
!====================================
Government demand for E/M commodities
====================================!

Variable
      (all, t, alltime)         gcet(t)
        # total gov't expenditure in value unit#;

Equation
E_gcee      # gov't purchase of energy commodity #
     (all, j, goods_e) (all, t, alltime)
     gcee (j, t) = gcet(t) - pry(j, t);
! The actual quantity form:
GCET(t) * S_V5E(t) * S_V5EE(j, t) = GCEE(j, t) * PRY(j, t) !

E_gceo      # gov't purchase of material commodity #
(all, j, goods_m) (all, t, alltime)
 gceo (j, t) = gcet(t) - pry(j, t);
! The actual quantity form:
 GCET(t) * S_V5M(t) * S_V5MM(j, t) = GCEO(j, t) * PRY(j, t) !

!==========================================================================
Government budget constraint
- assume no gov't deficit and issued bond
- gov't expenditure financed by tax revenue, including corporate short-run
  profit tax + HH income tax - investment tax credit - R&D tax credit
- gov't expenditure goes to pure consumption of commodity
===========================================================================!
!=================================
Corporate income tax revenue TAXC
=================================!

Coefficient
     (all, i, sectors) (all, t, alltime)  LPRF(i, t)
     # short-run profit of sector i #;
     (all, i, sectors) (all, t, alltime)  LTAXCI (i, t)
     # sector-specific corporate short-run profit tax revenue #;
     (all, t, alltime)  LTAXC (t)
     # aggregate corporate short-run profi tax revenue #;

Formula
     (all, i, sectors) (all, t, alltime)
     LPRF(i, t) = V1_Q(i, t) - V1_E(i, t) - VL(i, t) - V1_M(i, t);
     ! original form of short-run profit: PRF = OUP*PRP - ENT*PRE - LAB*WAG
     - OIN*POI, expressed in TABLO using the value coefficient in IO table !
     (all, i, sectors) (all, t, alltime)
     LTAXCI (i, t) = TCOR(t) * LPRF(i, t);
     (all, t, alltime)
     LTAXC (t) = sum {i, sectors, LTAXCI(i, t)};

Variable
    (all, i, sectors) (all, t, alltime)  prf(i,t)
     # short-run profit of sector i #;
    (all, i, sectors) (all, t, alltime) taxci(i,t)
     # sector-specific corporate short-run profi tax revenue #;
    (all, t, alltime)                    taxc(t)
    # aggregate corporate short-run profi tax revenue #;

Equation
E_taxc      # aggregate corporate short-run profi tax revenue#
     (all, t, alltime)
     taxc (t) = sum{i, sectors, LTAXCI(i,t) / LTAXC(t) * taxci(i,t)};
E_taxci     # corporate short-run profi tax revenue from sector i #
     (all, i, sectors) (all, t, alltime)
     taxci (i, t) = 100 / TCOR(t) * delTCOR(t)  + prf(i,t);
E_prf     # short-run profit of sector i #
     (all, i, sectors) (all, t, alltime)
prf(i, t) = V1_Q(i,t) / LPRF(i,t) * [oup(i,t) + prp(i,t)]
          - V1_E(i,t) / LPRF(i,t) * [ent(i,t) + pre(i,t)]
          - VL(i,t) / LPRF(i,t) * [lab(i,t) + wag(t)]
          - V1_M(i,t) / LPRF(i,t) * [oin(i,t) + poi(i,t)];
```

```
!===========================
HH income tax revenue TAXH
===========================!
Coefficient
(all, t, alltime)  LTAXH(t)  # HH income tax revenue # ;

Formula
(all, t, alltime)  LTAXH(t) = TINC(t) * V_L(t) ;
! TAXH(t) = TINC(t) * WAG(t) * sum{i, sectors, LAB(i,t)} = TINC(t) * V_L(t) !

Variable
(all, t, alltime)  taxh(t)  # HH income tax revenue # ;

Equation
E_taxh   # HH income tax revenue #
(all, t, alltime)
taxh(t) = 100 / TINC(t) * delTINC(t)
     + wag(t)
     + sum{i, sectors, S_VL(i, t) * lab(i, t)};

!==========================
Investment tax credit TAXI
===========================!

Coefficient
(all, i, sectors) (all, t, alltime)   LTAXII(i, t)
 # sector i's investment tax credit #;
(all, t, alltime)  LTAXI(t)
 # gov't revenue loss from investment tax credit #;

Formula
(all, i, sectors) (all, t, alltime)
LINV(i,t) = LJNV(i,t) * [ 1 + (PHI/2) * (LJNV(i,t) / LCAP(i,t))];
(all, i, sectors) (all, t, alltime)
LTAXII(i,t) =TITC(t) * LINV(i,t) * LPRII(t);
(all, t, alltime)
LTAXI(t) = sum {i, sectors, LTAXII(i,t)};
Variable
(all, i, sectors) (all, t, alltime)  taxii(i, t)
 # sector i's investment tax credit #;
(all, t, alltime)                    taxi(t)
 # gov't total revenue loss from investment tax credit #;

Equation
E_taxii   # sector i's investment tax credit #
(all, i, sectors) (all, t, alltime)
 taxii(i, t) = 100 /TITC(t) * delTITC(t) + inv(i, t) + prii(t) ;
!delTITC(t), inv(i,t), prii(t) defined in producer demand for investment good !

E_taxi   # total revenue loss from investment tax credit #
(all, t, alltime)
taxi(t) = sum{i, sectors, LTAXII(i, t) / LTAXI(t) * taxii(i, t)};
! total investment tax credit TAXI(t) = sum {i, sectors, TAXII(i,t)},
the percentage change form:
TAXI(t) * taxi(t) = sum{i, sector, TAXII(i,t) * taxii(i, t)} !

!=======================
R&D tax credit TAXR
=======================!

Coefficient
(all, i, sectors) (all, t, alltime)
 LTAXRI(i,t)   # sector i' s R&D tax credit #;
(all, t, alltime)
 LTAXR(t)    # gov't revenue loss form R&D tax credit #;

Formula
(all, i, sectors) (all, t, alltime)
LTAXRI(i,t) = TRTC(t) * LRNV(i,t) * LPRRR(t);
(all, t, alltime)     LTAXR(t) = sum {i, sectors, LTAXRI(i,t)};
```

```
Variable
(all, i, sectors) (all, t, alltime)
taxri(i,t)     # sector i' s R&D tax credit #;
(all, t, alltime)
taxr(t)    # gov't revenue loss form R&D tax credit #;

Equation
E_taxri   # sector i's R&D tax credit #
(all, i, sectors) (all, t, alltime)
taxri(i,t) = 100 /TRTC(t) *delTRTC(t) + rnv(i, t) + prrr(t);
! delTRTC(t), rnv(i,t), prrr(t) all defined in producer demand for R&D good
LTAXR is the defacto gov't expenditure on providing R&D fund,
viz. gov't subsidy to R&D investment!

E_taxr  # total R&D tax credit #
(all, t, alltime)
taxr(t) = sum {i, sectors, LTAXRI(i, t) / LTAXR(t) * taxri(i, t)} ;
!==============================
total gov't tax revenue TAXT
==============================!

Coefficient
   (all, t, alltime)   LTAXT(t)     # total tax revenue collected by gov't #;
Formula
   (all, t, alltime)  LTAXT(t) = LTAXC(t) + LTAXH(t) - LTAXI(t) - LTAXR(t);
Variable
   (all, t, alltime)  taxt(t)      # total tax revenue collected by gov't # ;
Equation
E_taxt      # total tax revenue collected by gov't #
   (all, t, alltime)
 taxt(t) = LTAXC(t)/LTAXT(t) * taxc(t) + LTAXH(t)/LTAXT(t) * taxh(t)
 - LTAXI(t)/LTAXT(t) * taxi(t) - LTAXR(t)/LTAXT(t) * taxr(t) ;
!===================================================================
Gov't budget constraint: gov't tax revenue LTAXT used to afford
gov't expenditure on commodity consumption LGCET
===================================================================!

Equation
E_gcet       # total gov't expenditure #
(all, t, alltime) gcet(t) = taxt(t);
!gov't budget constraint: LGCET(t) = LTAXT(t)!

!=============================================
export demand for energy/material commodities
=============================================!

Coefficient
(parameter)(all, j, goods_e)    EXP_ELAST_E(j)
 # energy commodity export elasticity #;
(parameter)(all, j, goods_m)    EXP_ELAST_M(j)
 # material commodity export elasticity #;

Read
EXP_ELAST_E from file Basedata header  "EXPE";
EXP_ELAST_M from file Basedata header  "EXPM";

Equation
E_exqe   # export demand for energy commodities #
(all, j, goods_e) (all, t, alltime)
exqe(j,t) = ouy(j,t) + EXP_ELAST_E (j) * pry(j,t);

E_exqo   # export demand for material commodities #
(all, j, goods_m) (all, t, alltime)
exqo(j,t) = ouy(j,t) + EXP_ELAST_M (j) * pry(j,t);

!============================================
```

```
Market clearing condition for E commodities
==========================================!
Equation
E_mkte    # market clearing condition for energy commodities #
(all, j, goods_e) (all, t, alltime)
ouy(j, t) = V2E(j, t)/V1_Y(j, t) * cone(j, t)
          + V3E(j, t)/V1_Y(j, t) * iine(j, t)
          + V4E(j, t)/V1_Y(j, t) * rrne(j, t)
          + V5E(j, t)/V1_Y(j, t) * gcee(j, t)
          + V6E(j, t)/V1_Y(j, t) * exqe(j, t)
          + sum {i, sectors, V1E(j, i, t)/V1_Y(j, t) * en(j, i, t)} ;

!============================================
Market clearing condition for M commodities
===========================================!
Equation
E_mkto    # market clearing condition for material commodities #
(all, j, goods_m) (all, t, alltime)
ouy(j, t) = V2M(j, t)/V1_Y(j, t) * cono(j, t)
          + V3M(j, t)/V1_Y(j, t) * iino(j, t)
          + V4M(j, t)/V1_Y(j, t) * rrno(j, t)
          + V5M(j, t)/V1_Y(j, t) * gceo(j, t)
          + V6M(j, t)/V1_Y(j, t) * exqo(j, t)
          + sum {i, sectors, V1M(j, i, t)/V1_Y(j, t) * oi(j, i, t)} ;

!=================================================
Market clearing condition for raw investment good
=================================================!
Coefficient
(all, t, alltime)     LINVT(t)      # total raw investment demand # ;

Formula
(all, t, alltime)     LINVT(t) = sum{i, sectors, LINV(i, t)} ;

Equation
E_mkti    # market clearing condition for raw investment good#
(all, t, alltime)
invt(t) = sum{i, sectors, LINV(i, t)/LINVT(t) * inv(i,t)};
!LHS: the output of investment sector, supply of raw investment good.
 RHS: the producer demand for raw investment good!


!==========================================
Market clearing condition for raw R&D good
==========================================!
Coefficient
(all, t, alltime)      LRNVT(t)      # economy-wide R&D investment #;

Formula
(all, t, alltime)      LRNVT(t) = sum{i, sectors, LRNV(i,t)};

Equation
E_mktr    # market clearing condition for raw R&D good#
(all, t, alltime)
rnvt(t) = sum{i, sectors, LRNV(i,t)/LRNVT(t)*rnv(i,t)};

!==================================
Market clearing condition for labor
==================================!
Variable
(all, t, alltime)  labt(t) # percentage change in total labor supply #;

Equation
E_mktl     # market clearing condition for labor #
 (all, t, alltime)  labt(t) = sum{i, sectors, S_VL(i, t) * lab(i, t)};
```

Chapter 4

Can China Harness Globalization to Reap Domestic Carbon Savings? Modelling International Technology Diffusion in a Multi-region Framework*

Abstract: The paper examines the effect of globalization, particularly international technology diffusion (ITD), on China's domestic carbon savings. Building on a multi-region numerical model, this study considers both indigenous R&D and foreign TD as two sources of endogenous TC for domestic carbon savings. The model systematically describes foreign TD through three diffusion channels of trade, foreign direct investment (FDI), and disembodied spillovers, with an elaborate treatment on local knowledge absorptive capacity. Simulation results show that: (1) Foreign knowledge inflows complements China's indigenous R&D investments to help curb domestic carbon emissions, with the leading diffusion channel being disembodied spillovers in the short run and embodied diffusion (via import and FDI) in the long run; (2) Trade and FDI liberalization (commodity globalization) facilitates economic integration and production growth, but at the cost of higher emissions levels without carbon savings from ITD; (3) Removal of the barriers of transferring technologies by advanced economies (knowledge globalization) can realize the benefits of domestic carbon savings (through ITD). (4) Domestic climate regulations can give rise the compensating effect by inducing indigenous R&D and foreign knowledge inflows in the domestic economic composition, hence helping partially mitigate disincentive global trends.

Keywords: Globalization; International technology diffusion; Climate policy modelling

* This chapter is based on the paper that is invited revisions in Energy Economics as Jin, W., "Can China harness globalization to reap domestic carbon savings? Modelling international technology diffusion in a multi-region framework."

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4.1 Introduction

In formulating prudent strategies to combat global warming, emissions from every corner of the world must be considered due to the global nature of climate stabilization (IEA, 2010; Stavins, 2011). Although most emission abatement obligations rest with the industrialized countries, it is likely that many low-cost mitigation opportunities exist in the developing world. In particular, the emerging economies call for international technology transfers to support indigenous efforts, so that the climate compliance cost can be mitigated (IPCC, 2000; World Bank, 2008; Popp, 2011; Freitas et al., 2012).

While the traditional paradigm of international technology transfers (e.g., North-South Official Development Assistance) may be useful for climate negotiating agenda (UNFCCC, 2007a), it has become increasingly flawed due to a narrow conceptualization of the nature, size, scope and method of technology diffusion (TD). The paradigm that emphasizes the role of government neglects the normal working of market force in the process of TD, which fundamentally brings about the current impasse of climate negotiations and slow progress of low-carbon technology transfers (Brewer, 2008, 2009; Gupta et al., 2007).[1]

To break the impasse, there is a dire need for climate technology strategies to reorient the decentralized market and private sector as the key force to mobilize international TD. This pivot is particularly necessary in the current context of globalization (World Bank, 2008; Popp, 2011). On the one hand, as the traditional aspect of globalization (production globalization), national economies are increasingly integrated into an interdependent world economy through multilateral trade and investment, the globalized network of production and distribution enables an extensive dissemination of technologies via cross-border transactions of material, capital, and products (Wolf, 2005; Stiglitz, 2006; UNCTAD, 2010a). On the other hand, as the modern aspect of globalization (innovation globalization), internationalization of R&D enhances a tendency for higher reliance of indigenous innovation on external knowledge sources, both developed and developing nations have

[1] Put another way, technology is at the hand of private sectors and can't be transferred at will by the government. As a result, the magnitudes of ODA programs remain quite small relative to private investments. FDI are on the order of hundreds of billions of dollars per year, as compared with total ODA flows on the order of hundreds of millions (World Bank, 2007; UNFCCC, 2007a). Private financial contribution is essential for leveraging investments for a low-carbon economy, in view of huge public fiscal deficits worldwide (UNCTAD, 2010b).

leveraged the international heightened mobility of ideas for building domestic knowledge stock (OECD, 1997; Archibugi and Michie, 1995, 1997; Archibugi and Iammarino, 1999; UNCTAD, 2005).

Clearly, the globalization creates an opportunity of low-carbon TD and carbon savings for the world's largest carbon emitter - China. To decouple carbon emissions from economic growth, this nation has stepped up efforts to change its development pattern by boosting technological innovation (MOST, 2006). Albeit strong growths in indigenous R&D, China's indigenous innovation does not necessarily signal an abandonment of the "open door" policy. Instead, China seeks to leverage the growing globalization to reinforce its innovative capacities. First, Beijing begins to attach the same importance to imports as exports in its foreign trade policy, with the purpose of importing foreign high-tech products and absorbing embodied technologies (WTO, 2010; IMF, 2011). Second, China's rapid expansion of higher education has reshaped global distribution of human capital, which fosters a transition of inward FDI into modern high-tech investment and hence a dispersion of technologies (UNCTAD, 2005). Thirdly, innovation globalization has created an international mobility of ideas through scientific papers, patent, technical conference, and academic networking. The worldwide spread of disembodied knowledge thus favors technology learning and absorption by China (OECD, 1997; Freeman, 2006; 2010).

Therefore, in such a context where China's integration into the globalized economy not only stimulates growth momentum but also provides an opportunity of knowledge diffusion, both of which have significant impacts on China's environmental performance. It is thus vital to explore the effect of globalization, particularly international TD, on China's carbon saving potential. In explicit, we attempt to address the following issues: 1) What's the contribution of indigenous R&D and foreign TD to China's domestic carbon savings; 2) Through which channels does China acquire foreign knowledge to complement indigenous innovation; 3) How knowledge absorptive capacity affect assimilation of foreign diffused technologies; 4) Which policies can be designed to harness the beneficial effects of globalization for domestic carbon savings; 5) Can domestic climate regulations induce international knowledge inflows to help lower climate compliance costs.

To address these issues, we incorporate the mechanism of endogenous technical change (TC) into a multi-sector, multi-region CGE numerical model. The "stock of knowledge" approach is used to explicitly represent technology in the spirit of Goulder and Schneider (1999) and Sue Wing (2001).[2] To advance the existing modeling literature that only considers indigenous innovation within a closed economy, we attempt to extend the single-country structure into a multi-region one, so that the mechanism of cross-nation knowledge diffusion can be explicitly examined. Such an effort is necessary, because with technology transfer placed high upon climate policy agenda, there is a pressing need for researchers to examine the potentials of international TD to facilitate low-carbon innovation. Modeling international TD thus becomes a fruitful avenue for future climate policy analysis (Grubb et al., 2002; Popp, 2006a; Gillingham et al., 2008; Popp et al., 2010b; Hübler, 2011).[3]

To our knowledge, only a few studies exist that considers international TD in current climate policy modeling literature. Gerlagh and Kuik (2007) use the GTAP-E model to investigate a mechanism of technology spillovers through the transfers of price-induced energy-saving TC. Hübler (2011) develops a recursive-dynamic CGE model to examine a mechanism of international TD through FDI. Leimbach and Baumstark (2010) (also in Leimbach and Edenhofer (2007) and Leimbach and Eisenack (2009)) provides a multi-region framework to model TD embodied in foreign trade. Methodologically, these studies adopt the implicit (parametrical) approach to represent technology, where the mechanism of TD is described as productivity parameter growth as an outcome of underlying drivers (e.g., trade and FDI). In contrast, other studies choose the "stock of knowledge" approach to explicitly represent technology, where the mechanism of TD is described as the spillover of foreign knowledge into domestic knowledge stock. For example, Bosetti et al. (2008, 2011) explore the mechanism of disembodied knowledge spillover that augments domestic knowledge assets. Buonanno et al. (2003) consider modeling a stock of global knowledge that generates international knowledge spillover into individual countries.[4]

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[2] The explicit method of representing technology has theoretical origins in endogenous growth literature, which demonstrates the link between knowledge and technical progress (Romer, 1990; Aghion and Howitt, 1998; Acemoglu, 2002, 2009). Along this direction, this is a growing trend in climate policy analysis to model technology using the "stock of knowledge" approach (e.g., Goulder and Schneider, 1999; Nordhaus, 2002; Buonanno et al., 2003; Popp, 2004; Sue Wing, 2006; Löschel and Otto, 2009; Acemoglu et al., 2009; Jin, 2012).

[3] Most of existing literature focus on empirical evidences on environmentally friendly TD (e.g., Lanjouw and Mody, 1996; Popp, 2006b; Dechezleprêtre et al., 2008; Johnstone et al., 2010; Popp et al., 2010a; Lovely and Popp, 2011), but numerical modeling in this field are still not sufficient.

[4] The literature also includes studies that model international technology transfer through direct financial transfers from donor to recipient countries for climate mitigation (e.g., Yang and

While providing insights into the TD mechanism, current modeling studies only capture one single type of TD channel in isolation.[5] It is thus needed to develop a comprehensive framework that models various conduits of TD and their combined effect. To fill this gap, this paper contributes to climate policy modeling in the following ways: (1) An *innovation possibility frontier (IPF)* is used to explicitly represent both indigenous R&D and international TD as dual sources of domestic knowledge creation; (2) A systematic modeling framework is developed to capture international TD through the channels of trade, FDI, and disembodied knowledge spillovers; (3) An elaborate treatment of knowledge absorptive capacity is presented to describe technology appropriateness (compatibility between foreign transferred technology and local technical condition).

This chapter is organized as follows: Section 4.2 describes the modeling framework, with an emphasis on modeling international TD through various channels. Section 4.3 discusses model calibration and implementation. Simulation results and discussions are presented in Section 4.4. Section 4.5 concludes.

4.2 Model Description

4.2.1 Basic Framework

The basic framework is a multi-region, multi-sector intertemporal optimization CGE model.[6] It distinguishes six world countries/regions, including: China (CHN), USA, Japan (JPN), Western Europe (EUW), the rest of the industrialized countries (RIN), and the rest of the world (ROW).[7] Economic system in each region is represented by multiple agents, including: Twelve production sectors, an investment sector (producing physical capital goods), a R&D sector (producing R&D good), a representative household and a government. To be relevant to climate policy studies, the twelve production sectors consist of five energy sectors and

Nordhaus, 2006; Kypreos and Turton, 2011). For a critique of this method, see Popp (2009).

[5] As shown in some empirical studies (e.g., Clerides et al., 1998; Keller, 2004), private firms do not merely conduct a single type of economic activity associated with TD, but perform several such activities simultaneously.

[6] As compared to the recursive-dynamic models, intertemporal optimization CGE models feature an endogenous treatment of the intertemporal behavior of forward-looking agents, with their current decisions depending on expectation about future economic conditions (Jorgenson and Wilcoxen, 1990; Bovenberg and Goulder, 1996; McKibbin and Wilcoxen, 1998; Dixon et al., 2005).

[7] For the country composition of each world region, see Appendix 4.A.

seven non-energy sectors.[8] Carbon emissions are calculated based on carbon intensities of fossil fuel inputs (coal, oil and natural gas) used in intermediate production and final use.

Economic behaviors of multiple agents within each region are modeled in line with the general equilibrium structure, which outlines input-output (IO) circular flows of multiple commodities and primary factors within the economy (see Fig. 3.1 in Chapter 3). There are 12 produced commodities and corresponding production sectors, indexed by the row subscript $j\,(j=1,2,\ldots,12)$ and the column subscript $i\,(i=1,2,\ldots,12)$, respectively; 3 types of primary factors (labor, physical capital, knowledge capital), indexed by the subscript $f\,(f=L,K,H)$; 5 types of final use (consumption, investment, R&D, government, export), indexed by the subscript $d\,(d=C,I,R,G,X)$. Intersectoral transactions in intermediate productions are represented by the $j\times i$ matrix; Inputs of primary factors in production are indicated by the $f\times i$ matrix; Final uses of produced commodities are represented by the $j\times d$ matrix.

From this IO framework to a CGE model, I describe the decision problems facing these economic agents and characterize their behaviors in a decentralized equilibrium condition.[9] To endogenously represent TC, the model broadens the traditional CGE structure by adding R&D investment and knowledge input. This will be articulated in the following sections.

4.2.2 Endogenous Technical Change

In the spirit of Goulder and Schneider (1999) and Sue Wing (2001), this study adopts the "stock of knowledge" method to explicitly represent technology, because TC per se is a reconfiguration of production factors as a result of applying new knowledge (e.g., technical know-how, managerial skills) in production. A representation of knowledge as a production input can thus give insights into its effect on production TC. In explicit, knowledge is treated as an accumulated stock of economically useful asset which is augmented by indigenous R&D and foreign TD. The accumulated knowledge stocks are then applied in production to facilitate a reconfiguration of production factor inputs for productivity growth (the rate of production TC). Simultaneously, the use of knowledge inputs leads to a substitution for physical inputs such as labor, energy and materials (the bias of production TC).

[8] For the model sectoral classification and mapping, see Appendix 4.A.

[9] Specification and characterization of the problem faced by economic agents within each foreign country is similar to the modeling framework presented in Chapter 3 Appendix 3.B, except for the specification of international technology diffusion into China as described in Section 4.2.4.

To model this endogenous TC mechanism, I specify the production technology as a separable KLEM-H nested CES function (see Fig. 3.2 in Chapter 3). That is, for a given sector i producing output Q_i,[10] knowledge capital H_i substitutes for a composite of physical inputs Z_i, which is in turn made up of primary factor of physical capital K_i and labor X_{iL}, as well as intermediate commodity inputs of energy bundle X_{iE} and material bundle X_{iM}. X_{iE} comprises five energy goods X_{ij}^{E}, and X_{iM} is composed of seven non-energy goods X_{ij}^{M}. Given this production technology, the producer problem specific to sector i is formulated as:

$$\max \ V_i(t)=\int_t^{\infty}\exp\left[-\int_t^{s} r(s')\cdot ds'\right]\cdot\Pi_i(s)\cdot ds \tag{4.1}$$

$$\text{s.t. } \Pi_i(t)=(1-\tau_Q)\cdot P_i(t)\cdot Q_i(t)-P_{iL}(t)\cdot X_{iL}(t)-(1+\tau_C)\cdot P_{iE}(t)\cdot X_{iE}(t)-P_{iM}(t)\cdot X_{iM}(t)$$
$$-(1-\tau_I)\cdot P_{iI}(t)\cdot I_i(t)-(1-\tau_R)\cdot P_{iR}(t)\cdot R_i(t) \tag{4.2}$$

$$\dot{K}_i(t)=J_i(t)-\delta_K\cdot K_i(t) \tag{4.3}$$

$$I_i(t)=\varphi_i\left[J_i(t),K_i(t)\right]=J_i(t)\cdot\left[1+\frac{\psi}{2}\cdot\frac{J_i(t)}{K_i(t)}\right] \tag{4.4}$$

$$\dot{H}_i(t)=\hbar\left[R_i(t),H_i(t),R_i^{*}(t)\right] \tag{4.5}$$

where the firm's objective is to optimally choose the inputs of labor X_{iL}, energy X_{iE}, material X_{iM}, physical capital investment I_i and R&D investment R_i to maximize an intertemporal profit stream V_i, subject to the technology constraints. In Eq. (4.1), V_i is formulated as a discounted present value of future profit streams from time t to an infinite future, with real interest rate r as discounting factor. In Eq. (4.2), current profit flow Π_i equals output revenues minus input costs, with $\tau_Q,\tau_C,\tau_I,\tau_R$ being corporate income tax, carbon tax on fossil energy inputs, investment tax credit and R&D tax credit, respectively.

Eq. (4.3) specifies the law of motion of physical capital stock K_i, its accumulation depends on fixed capital investment J_i and the rate of capital depreciation δ_K. Eq. (4.4) models the capital investment process that is subject to imperfect capital mobility and investment adjustment cost (Goulder and Schneider, 1999; McKibbin and Wilcoxen, 1999).[11]

[10] For ease of exposition, we have not subscripted variables by country notation.

[11] In explicit, to install J_i unit of capital, a firm must buy a larger amount of raw investment

Eq. (4.5) is the *IPF* that describes the knowledge creation process, where accumulation of domestic knowledge stock $\dot{H}_i$ depends on indigenous R&D R_i, existing knowledge stocks H_i and international TD R_i^*. As Fig. 4.1 illustrates, in modeling the pattern of international TD I only consider unidirectional knowledge spillovers from technologically advanced countries to China.[12] Accordingly, I assume that TC in each foreign country is driven by indigenous R&D, with the *IPF* degenerated as $\dot{H}_i(t) = \hbar[R_i(t), H_i(t)]$ without international TD R_i^*.[13] In contrast, TC in China depends on both indigenous R&D and foreign TD, with its *IPF* remained as Eq. (4.5).[14] Before providing an explicit representation of the *IPF* in Section 4.2.5, we will examine the dual sources of innovation and endogenous TC - indigenous R&D (in Section 4.2.3) and international TD (in Section 4.2.4), to which I now turn.

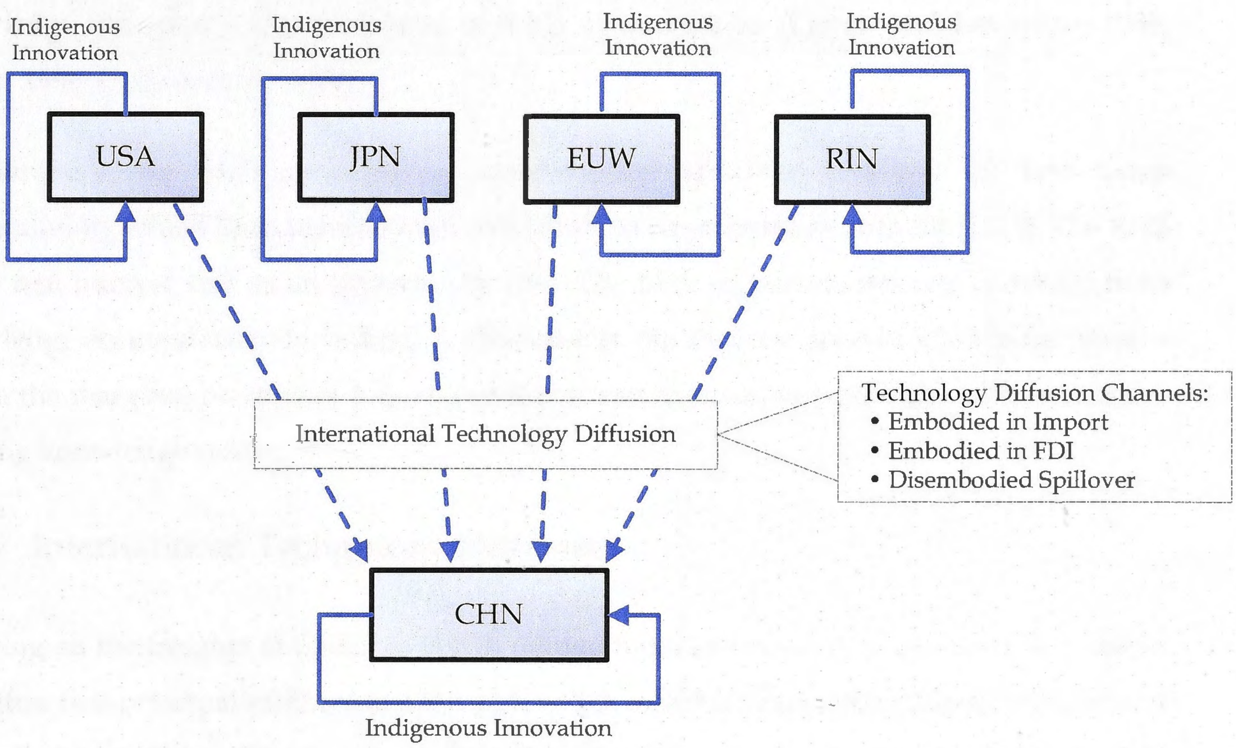
goods I_i that depends on the rate of investment J_i/K_i and adjustment cost coefficient ψ.

[12] For the sake of model tractability, we surpass multidirectional knowledge spillovers and interaction which may involves computing a Nash Equilibrium. For example, see Leimbach and Baumstark (2010).

[13] This is according to the path dependence of innovation in technologically advanced nations, where technological progress tends to move along independent path with innovation pattern embedded in local specific socio-technological circumstances (Rosenberg, 1994; Bosetti et al., 2008; Acemoglu, 2009).

[14] Due to a backward position in the global technology ladder, innovations in developing countries can largely benefit from their knowledge gap relative to technologically advanced countries and knowledge diffusion (Gerschenkron, 1962; Acemoglu, 2009).

Figure 4.1: Pattern of international technology diffusion: Unidirectional knowledge diffusion from technologically advanced foreign countries to China



Note: Unidirectional technology diffusion from technologically advanced foreign countries to China, through three diffusion channels (trade, FDI, disembodied knowledge spillover)

4.2.3 Indigenous R&D Investment

To capture indigenous innovation, we solve the producer problem outlined in Eqs. (4.1)-(4.5), and characterize the behavior of indigenous R&D investments as follows:

$$(1-\tau_R)\cdot P_{iR}(t)=\lambda_{iH}(t)\cdot\frac{\partial\hbar[R_i(t),H_i(t),R_i^*(t)]}{\partial R_i(t)} \tag{4.6}$$

$$\frac{\dot{\lambda}_{iH}(t)+(1-\tau_Q)\cdot P_i(t)\cdot\frac{\partial Q_i(t)}{\partial H_i(t)}+\frac{\partial\hbar[R_i(t),H_i(t),R_i^*(t)]}{\partial H_i(t)}}{\lambda_{iH}(t)}=r(t) \tag{4.7}$$

where Eq. (4.6) is the optimality condition of indigenous R&D investment R_i, instructing R&D investment of private firms to reach an equilibrium level where marginal cost (LHS) is equal to marginal benefit (RHS). The marginal cost comes from expenditures on purchasing an extra unit of R&D goods. The marginal benefit involves the shadow price of knowledge capitals λ_H and innovation possibility gain.[15] In particular, the innovation possibility gains from R&D investment can be harvested from two sources: Indigenous R&D not only create in-house knowledge, but also enhance indigenous capacity to assimilate international knowledge diffusion – the dual faces of R&D in innovation (Cohen and Levinthal, 1989; Keller, 1996; Griffith et al., 2000).

Similarly, Eq. (4.7) provides an intertemporal arbitrage condition of knowledge accumulation, which instructs marginal cost (RHS) to equal marginal benefit (LHS). The RHS is the real interest rate as an opportunity cost. The LHS represents the rate of return from knowledge accumulation, including: An increase in the shadow price of knowledge asset, a rise in the marginal product of knowledge input, and innovation possibility gain from more existing knowledge stocks.

4.2.4 International Technology Diffusion

Drawing on the insights of Griliches (1979) on two types of knowledge spillovers, our model identifies two principal mechanisms through which external knowledge diffuse into China: 1) Embodied knowledge diffusion through indirectly using knowledge-embodied intermediate and capital goods; 2) Disembodied knowledge diffusion through directly learning disembodied knowledge spillovers.[16]

Embodied knowledge diffusion (passive knowledge diffusion) occurs when domestic firms indirectly benefit from external innovation by using knowledge-embodied foreign intermediate commodity (via import) or capital goods (via FDI). [17] Embodied TD has its

[15] The shadow price of knowledge capital is determined according to the "Tobin's-q" investment theory, with the shadow price denoting the increments to the equity value of the firm from investing an additional unit of capital (Tobin, 1969; Summers, 1981; Goulder and Schneider, 1999; McKibbin and Wilcoxen, 1999).

[16] Identification of these two mechanisms stems from the basic distinction between codified and tacit knowledge. Codified knowledge is explicit knowledge that is embodied in specific physical products, while tacit knowledge is the personalized knowledge that is virtually impossible to make explicit through embodied mechanism (Hayek, 1945; Polanyi, 1958; Arrow, 1969). While application of efficient physical products can advance capital vintage of production technology in recipient countries, there is also a need to learn and absorb disembodied knowledge for building an indigenous capacity of innovation (IPCC, 2000; Stern, 2007).

[17] Embodied TD corresponds to the first type of knowledge spillovers identified by Griliches (1979): rent spillovers (purchase prices of imported intermediate input and capital goods do not completely embody the opportunity cost of producing the product that include R&D cost of

theoretical and empirical origins in the seminal work by Coe and Helpman (1995), indicating that international TD should be embodied in the flows of physical commodity transactions through the channels of international trade and investment.

In parallel, disembodied knowledge diffusion (active knowledge diffusion) involves direct learning and absorption of the disembodied forms of technologies (e.g., formulas, blueprints, patents), not necessarily linking to the economic transactions of physical goods.[18] Disembodied TD is rooted in the seminal works by Rivera-Batiz and Romer (1991) that suggests the key role of disembodied knowledge spillover externality in the process of international TD.

To describe the embodied and disembodied TD, Sections 4.2.4.1-4.2.4.3 provide a comprehensive framework to model three channels of TD, including: TD embodied in trade, TD embodied in FDI, and disembodied TD. Moreover, while knowledge can diffuse from abroad through these three channels, the efficiencies of assimilating the diffused knowledge of the recipient countries are determined by local knowledge absorptive capacity, which will be considered in Sections 4.2.4.4.

4.2.4.1 Technology Diffusion Embodied in Trade

TD embodied in trade refers to the process of knowledge diffusion through import flows. Imported goods and services (e.g., chemical products, electronic components and software) are used as intermediate inputs into the production in the host country for productivity growth. On the one hand, imports broaden input supply chains, creating an access to an expanding variety of intermediate inputs from abroad (variety-expanding effect of imports). On the other hand, the imported products embody foreign knowledge that can be assimilated by the host country to improve input efficiency (input-augmenting effect of embodied knowledge) (Eaton and Kortum, 2001, 2002; Amiti and Konings, 2007; Acharya and Keller, 2008).

In this sense, TD through the channel of trade comes from the diffusion of knowledge embodied in the imports of intermediate input commodities, with the embodied knowledge

foreign innovation).

18 Disembodied TD corresponds to the second type of knowledge spillovers identified by Griliches (1979): pure knowledge spillovers (learning of foreign disembodied technologies augments domestic knowledge stocks with the learning cost usually less than the original R&D cost of foreign innovator).

augmenting input use efficiency.[19] In other words, if we think of commodity imports as a vehicle of TD, then foreign knowledge is embodied in intermediate product imports, with the embodied knowledge being absorbed by the recipient country to accumulate knowledge. To describe this mechanism, I model China's import flows in line with the Armington structure, with the Armington composite of intermediate commodity being modeled as a CES aggregate of domestically-produced and imported component of that commodity as:

$$X_{i,j}(t)=\left[X_{i,j}^{D}(t)^{\frac{\sigma_j^T-1}{\sigma_j^T}}+X_{i,j}^{T}(t)^{\frac{\sigma_j^T-1}{\sigma_j^T}}\right]^{\frac{\sigma_j^T}{\sigma_j^T-1}} \tag{4.8}$$

where $X_{i,j}$ is the composite of intermediate input commodity j used in China's sector i. $X_{i,j}^{D}, X_{i,j}^{T}$ are the domestically-produced and imported component of that intermediate goods, respectively. Substitution between domestic and import component is governed by the Armington elasticity σ_j^T. Within our multi-country model that distinguishes China's multiple trading partners, the imported component of that intermediate input is further modeled as a CES composite of imports from all foreign source countries as:

$$X_{i,j}^{T}(t)=\left[\sum_r X_{i,j,r}^{T}(t)^{\frac{\sigma_j^{TT}-1}{\sigma_j^{TT}}}\right]^{\frac{\sigma_j^{TT}}{\sigma_j^{TT}-1}} \tag{4.9}$$

where $X_{i,j,r}^{T}$ is the import of intermediate input commodity j into China's sector i from foreign country r. Substitution among foreign countries is governed by the elasticity σ_j^{TT}.

First, solving the producer problem as outlined in Eqs. (4.1)-(4.5) characterize the levels of demand for intermediate input variety $X_{i,j}$. Next, by solving the problem of cost minimization associated with the Eqs. (4.8)-(4.9), I can optimally allocate the intermediate input demand ($X_{i,j}$) into its import composite ($X_{i,j}^{T}$) and import component from each foreign source country ($X_{i,j,r}^{T}$) as:

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[19] Empirical evidences of this TD pattern is recorded in the pioneering work by Coe and Helpman (1995) who found a statistically significant effect of bilateral trade on international TD. Other empirical studies also find the significant and positive link between a country's factor productivity and knowledge created by its trading partners (e.g., Coe et al., 1997; Keller, 1998, 2002; Xu and Wang, 1999; Pavcnik, 2002; Madsen, 2007).

$$X_{i,j}^{T}(t)=\left[\frac{P_j(t)}{P_j^{T}(t)}\right]^{\sigma_j^{T}}\cdot X_{i,j}(t) \tag{4.10}$$

$$X_{i,j,r}^{T}(t)=\left[\frac{P_j^{T}(t)}{P_{j,r}(t)\cdot(1+\tau_j^{T})}\right]^{\sigma_j^{TT}}\cdot X_{i,j}^{T}(t) \tag{4.11}$$

where P_j is China's market price of intermediate goods composite j. P_j^T is the ideal price index of imported component of intermediate goods j. [20] $P_{j,r}$ is the price of intermediate goods j supplied by foreign country r. τ_j^T is the rate of import tariff imposed on commodity j. $P_{j,r}\cdot(1+\tau_j^T)$ is China's import price of commodity j from the foreign country r.

As mentioned above, both import flows and knowledge embodiment intensity determine the amount of knowledge diffused through trade. So far Eq. (4.11) has estimated the imports of intermediate input goods from foreign exporting countries into China. I further introduce the other factor: intensity of knowledge embodied in imports, which represents the amount of knowledge that is embodied in each unit of import flows. In line with the embodied technology hypothesis, this intensity can be estimated as:[21]

$$RI_{j,r}^{T}(t)=\theta^{T}\cdot\frac{R_{j,r}(t)}{Y_{j,r}(t)} \tag{4.12}$$

where $RI_{j,r}^T$ denotes the intensity of knowledge embodied in intermediate goods j imported from foreign country r. This intensity is measured as a ratio between R&D expenditure ($R_{j,r}$) and production output ($Y_{j,r}$) in foreign exporting country r. $Y_{j,r}$ is the outputs specific to commodity j. $R_{j,r}$ is the amount of commodity j that is used for R&D investment.[22] $Y_{j,r}, R_{j,r}$ are both endogenously determined in modelling the foreign economy r. θ^T is an

[20] As the dual price function associated with the CES composite of imports, P_j^T can be expressed as a CES aggregate of the imported commodity price from foreign source country as:
$P_j^T(t)=\left[\sum_r (P_{j,r}(t)\cdot(1+t_j))^{1-\sigma_j^{TT}}\right]^{\frac{1}{1-\sigma_j^{TT}}}$

[21] *"Embodied technology hypothesis"* claims that intangible knowledge has to be embodied in specific tangible physical products in order to embody their economically useful characteristics (Schmookler, 1966; Terleckyj, 1974; Scherer, 1982; Papaconstantinou et al., 1998; Hauknes and Knell, 2009).

[22] By the same token, this variable also represents R&D investment expenditure spend by the corresponding sector that producing commodity j, since our model implementation impose a one-to-one correspondence between each industrial sector and its produced commodity.

exogenous parameter that indicates foreign barriers of exporting knowledge-intensive goods to China.[23]

Given the two determinants of TD through trade, we can model the diffusion of knowledge embodied in trade as a product of import flows ($X^{T}_{i,j,r}$) and embodied knowledge intensity ($RI^{T}_{j,r}$) as:

$$R^{T}_{i,j,r}(t) = X^{T}_{i,j,r}(t) \cdot RI^{T}_{j,r}(t) \tag{4.13}$$

where $R^{T}_{i,j,r}$ denotes knowledge embodied in the import of intermediate commodity j from foreign country r into China's sector i. Next, the total amount of knowledge embodied in import flows can be estimated as follows:

$$R^{T}_{i,j}(t) = \sum\nolimits_{r} R^{T}_{i,j,r}(t) \tag{4.14}$$

$$R^{T}_{i}(t) = \sum\nolimits_{j} R^{T}_{i,j}(t) \tag{4.15}$$

where by summing over foreign countries r, $R^{T}_{i,j}$ is knowledge embodied in the import of intermediate input commodity j into China's sector i. By summing over intermediate input varieties, I further capture the total amount of knowledge embodied in intermediate imports into China's sector i (R^{T}_{i}). Once diffusing into China (the recipient country) through import, the embodied knowledge R^{T}_{i} is assimilated for building domestic knowledge. This process will be incorporated into the *IPF* in Section 4.2.5.

4.2.4.2 Technology Diffusion Embodied in FDI

TD embodied in FDI refers to the diffusion of knowledge that is embodied in foreign investment inflows. In the process of FDI, foreign invested capitals are used as primary factor inputs into production in the host country for productivity gains.[24] On the one hand,

[23] We introduce this parameter for the purpose of undertaking policy experiments (e.g., easing technology transfer restriction) in knowledge globalization scenario in Section 4.4, where policy shock raises the value of this exogenous parameter.

[24] FDI is an investment of MNCs in a foreign country with the intention of gaining a degree of control over the firm's operation. MNCs will bring with advanced technologies and best practices in the operation of foreign affiliates. It differs from indirect portfolio investment where foreign

inward FDI can bring to the host country new varieties of hardware, machinery, equipment, and other capital goods, which advances the capital vintage of domestic production recipes (provision of physical capital). On the other hand, the advanced capital goods invested by foreign MNC affiliates embody foreign technology that can be learnt by domestic firms through sectoral linkages along the supply chain (diffusion of embodied knowledge) (Rodriguez-Clare, 1996; Blomström and Kokko, 1998; Javorcik, 2004; Lin and Saggi, 2007; Haskel et al., 2007; Blalock and Gertler, 2008).

In this sense, if I think of FDI as a vehicle of TD, then foreign knowledge is embodied in the foreign invested capital, with the embodied knowledge being absorbed by the recipient country for knowledge accumulation.[25] To model this mechanism, I postulate that both domestic and foreign investments contribute to China's physical capital formation, and capitals invested by domestic and foreign countries are imperfect substitutes (Petri, 1997; Markusen, 2002; Mai, 2005; Lejour et al., 2008). The physical capitals invested in China are thus modeled as a CES aggregate of domestic and foreign components of that capital goods as:

$$I_i(t) = \left[I_i^D(t)^{\frac{\sigma_I^F - 1}{\sigma_I^F}} + I_i^F(t)^{\frac{\sigma_I^F - 1}{\sigma_I^F}} \right]^{\frac{\sigma_I^F}{\sigma_I^F - 1}} \tag{4.16}$$

where I_i is the composite of capital goods invested in China's sector i. I_i^D, I_i^F are the domestic and foreign component of that capital good composite, respectively. Substitution between these two components is governed by the CES elasticity σ_I^F, indicating the joint venture requirements on foreign investments entry.[26] Within the multi-region model that distinguishes multiple FDI sources, the component of foreign-invested capital is further modeled as a CES composite of FDI from all foreign source countries:

firms purchases stocks/shares in other companies for financial reasons (UNCTAD, 2005).

[25] Empirical evidence for this kind of TD is recorded in the work by Blomström and Persson (1983) who found a statistically significant influence of FDI inflows on international TD. Other empirical studies also suggest that host countries benefit from knowledge diffused from MNC foreign affiliates, with FDI being a robust diffusion channel (e.g., Haddad and Harrison, 1993; Aitken and Harrison, 1999; Xu, 2000; Keller and Yeaple, 2009).

[26] A larger value of the CES elasticity implies a higher possibility of substitution between foreign and domestic varieties in investment activities (a lower joint venture requirement).

$$I_i^F(t)=\left[\sum_r I_{i,r}^F(t)^{\frac{\sigma_I^{FF}-1}{\sigma_I^{FF}}}\right]^{\frac{\sigma_I^{FF}}{\sigma_I^{FF}-1}} \tag{4.17}$$

where $I_{i,r}^F$ is the FDI inflows into China's sector i from foreign country r. Substitution between foreign countries is governed by the CES elasticity (σ_i^{FF}).

Solving the producer problem as outlined in Eqs. (4.1)-(4.5) characterizes the demand for capital investment I_i.[27] Next, by solving the problem of cost minimization associated with Eqs. (4.16)-(4.17), I can characterize the level of FDI composite (I_i^F) and the component from each foreign source country ($I_{i,r}^F$) as:

$$I_i^F(t)=\left[\frac{P_I(t)}{P_I^F(t)}\right]^{\sigma_I^F}\cdot I_i(t) \tag{4.18}$$

$$I_{i,r}^F(t)=\left[\frac{P_I^F(t)}{P_{I,r}(t)\cdot(1+\tau_I^F)}\right]^{\sigma_I^{FF}}\cdot I_i^F(t) \tag{4.19}$$

where P_I is China's market price of capital good composite. P_I^F is ideal price index of FDI composite.[28] $P_{I,r}$ is the price of capital goods invested by foreign country r. τ_I^F is the rate of preferable tax (fiscal incentive) offered to MNC affiliates for FDI. $P_{I,r}(t)\cdot(1+\tau_I^F)$ is the after-tax price of capital goods invested by foreign country r.

The specifications in Eqs. (4.18)-(4.19) reflect two basic determinants of FDI. 1) Economic fundamentals: FDI is driven by the incentives of market-seeking MNC to exploit economies of scales (Blomström and Kokko, 2003; Blonigen, 2005). As the levels of FDI are expressed as a function of output size of the sector where foreign capitals are installed, the sector-specific outputs reflect market size and economic fundamentals in the host country; 2) Fiscal incentives: Developing countries commonly base fiscal incentives on preferable tax to attract FDI, (Brewer and Young, 1997; Blomström and Kokko, 2003; UNCTAD, 2005). The favorable

[27] The optimal levels of physical capital investment can be characterized according to the Tobin's-q theory. For the details, see Appendix 3.B.

[28] As the dual price function associated with the CES composite of FDI, P_I^F can be expressed as a CES aggregate of foreign capital prices from foreign source country as:

$$P_I^F(t)=\left[\sum_r\left(P_{I,r}(t)\cdot(1+t_I)\right)^{1-\sigma_I^{FF}}\right]^{\frac{1}{1-\sigma_I^{FF}}}$$

FDI tax is set to lower the costs of installing foreign capital goods, thus facilitating the physical capital formation in the recipient countries.

As mentioned previously, both the level of FDI and knowledge embodiment intensity determine the amount of knowledge diffusion through FDI. So far the level of inward FDI has been estimated by Eq. (4.19), I further model the knowledge intensity of FDI (the amount of knowledge embodied in each unit of FDI inflows) as follows:

$$RI_{i,r}^{F}(t) = \theta^{F} \cdot \frac{R_{i,r}(t)}{Y_{i,r}(t)} \tag{4.20}$$

where $RI_{i,r}^{F}$ denotes the intensity of knowledge embodied in capital goods invested by foreign country r, measured as a ratio between R&D expenditure ($R_{i,r}$) and production output ($Y_{i,r}$) specific to sector i in foreign country r. θ^{F} is an exogenous parameter, representing foreign restrictions on technology transfer through FDI outflows.

Given the two determinants of TD through FDI, we can model the diffusion of knowledge embodied in FDI as a product of FDI inflows ($I_{i,r}^{F}$) and embodied knowledge intensity ($RI_{i,r}^{F}$) as:

$$R_{i,r}^{F}(t) = I_{i,r}^{F}(t) \cdot RI_{i,r}^{F}(t) \tag{4.21}$$

where $R_{i,r}^{F}$ denotes knowledge embodied in FDI inflows into China's sector i from foreign country r. By summing over foreign countries r, I estimate the knowledge embodied in FDI as:

$$R_{i}^{F}(t) = \sum_{r} R_{i,r}^{F}(t) \tag{4.22}$$

where R_{i}^{F} denotes the total amount of knowledge embodied in FDI inflow into China's sector i. Once diffusing into China via the channel of FDI, the embodied knowledge R_{i}^{F} can be absorbed for domestic knowledge accumulation, which will be described by the *IPF* in Section 4.2.5.

4.2.4.3 Disembodied Technology Diffusion

Disembodied TD occurs when disembodied pure knowledge (as a public good) spill over from technology frontier countries to the laggards due to the imperfect appropriability of knowledge, which does not necessarily link to the economic transactions of physical goods.

Learning and absorption of disembodied knowledge thus favors innovation in places different from where originally created (Romer, 1990; Rivera-Batiz and Romer, 1991; Jaffe and Trajtenberg, 1998; Eaton and Kortum, 1999; Lee, 2006).

In this context, I draw on the insights of Bosetti et al. (2008), and postulates that China is exposed to an international knowledge pool created by technology frontier countries. On the one hand, due to the heterogeneous nature of knowledge created by individual technologically advanced countries,[29] their aggregate knowledge constitutes the global pool of disembodied knowledge. On the other hand, because of a backward position in the global technology leader,[30] the technologically backward country has a knowledge gap relative to advanced nations, which creates the disembodied knowledge pool that can be absorbed by China. Thus, the disembodied knowledge that may spill over to China can be modeled as

$$R_i^D(t) = \theta^D \cdot \sum_r R_{i,r}(t) - R_i(t) \qquad (4.23)$$

where $\sum_r R_{i,r}$ is the aggregate of foreign R&D investment specific to sector i, summing over all foreign countries r. R_i is China's indigenous R&D investment in that sector. The R&D gap thus constitutes foreign disembodied knowledge that may spill over to China. θ^D is an exogenous parameter indicating the externality of disembodied knowledge spillovers, of which the value is regulated by patent policy in foreign countries. Once spilling over to China, the disembodied knowledge R_i^D can be absorbed for domestic knowledge creation, which will be described by the *IPF* in Section 4.2.5.

4.2.4.4 Knowledge Absorptive Capacity

So far the model has captured all three channels of international TD, the diffused knowledge, however, are not the "manna from heaven" that indiscriminately falls on the host country,

[29] This coincides with the path dependence of innovation. TC within technological advanced country tends to follow a specific path that is embedded in local socio-technological context, generating differentiated and heterogeneous technologies (Nelson, 1993; Rosenberg, 1994). For example, U.S. has competitive advantage in coal gaslification technology, E.U in renewable energy, Japan in energy efficiency equipments.

[30] This view was put forward by Gerschenkron (1962) in his seminal work *Economic Backwardness in Historical Perspective,* arguing that TC is a process where all countries move upwards along a technology ladder, with the innovator at the top and the laggards at the bottom. By adopting frontier technologies, the backward countries can catch up with the advanced countries at a relatively rapid pace (Acemoglu, 2009).

only a fraction can be effectively absorbed according to local socio-technological conditions, with the efficiencies of knowledge absorption by the recipient countries are highly localized in the real practice of technology transfer.[31] The benefits of knowledge diffusion can be realized only if the recipient country builds indigenous capacity of knowledge absorption.

Accordingly, we distinguish two factors that influence knowledge absorptive capacity. 1) Indigenous R&D: host countries need to undertake R&D investment to enhance indigenous capacity for absorbing foreign diffused technologies (Cohen and Levinthal, 1989; Keller, 2004; Bosetti et al., 2008); 2) Structural characteristics: the host countries also need to improve structural characteristics (e.g., R&D intensity) of production technology, so that a match can be achieved between the transferred technologies and local technical sophistication levels (Atkinson and Stiglitz, 1969; Basu and Weil, 1998; Acemoglu, 2009). To represent these two factors, we model the knowledge absorptive capacity as:

$$\gamma_i(t) = \gamma_i^{RD}(t) \cdot \gamma_i^{SS}(t) = \frac{R_i(t)}{\sum_r R_{i,r}(t)} \cdot \exp\left[-\left|\frac{d_i(t)-\bar{d}_i(t)}{d_i(0)-\bar{d}_i(0)}\right|\right] \tag{4.24}$$

where, for any given sector i, knowledge absorptive capacity γ_i is expressed as a product of indigenous R&D index γ_i^{RD} and structural characteristics index γ_i^{SS}, implying their complementary roles in affecting knowledge absorptive capacity. γ_i^{RD} is modeled as a ratio of China's indigenous R&D to foreign R&D totals, indicating China's technological distance relative to the global technology frontier.[32] In specifying γ_i^{SS}, R&D intensity (R&D to output ratio) is used to indicate the structural characteristics of production technology.[33] $d_i(t)$ is R&D intensity specific to Chinas' sector i at period t, and $\bar{d}_i(t)$ is the average of R&D intensity among foreign advanced countries $\bar{d}_i(t) = (1/N) \cdot \sum_{r=1}^{N} d_{i,r}(t)$. $d_i(0)-\bar{d}_i(0)$ is structural

[31] This "localness" is reflected by the mismatch between transferred technology and locality in developing countries. For an articulation on the inappropriateness of technologies and its effect on productivity difference across nations, see Acemoglu (2009).

[32] As mentioned in Section 4.2.3 on the dual face of indigenous R&D, such a specification reflects the second face: indigenous R&D can reinforce domestic capacity to absorb and exploit foreign diffused knowledge (Cohen and Lethvinal, 1989; Keller, 1996).

[33] Structural similarity index reflects the degree to which foreign-created knowledge is targeted to local structural characteristics of production techniques (Acemoglu, 2009). For example, German manufacturing sector has higher R&D intensity level as compared with China, implying that the technology of German produced products, once introduced into China, is less targeted to China's less sophisticated production recipe, so that the embodied knowledge can't be fully absorbed.

difference in production technology between China and foreign countries at initial period. The exponential function scales the structural difference on a unit interval index.[34]

4.2.5 Synthesis of Innovation Possibility Frontier

Having examined both indigenous innovation and international TD in Sections 4.2.3-4.2.4, I synthesize the two sources of endogenous TC and formulate the *IPF* (innovation process) as:

$$\dot{H}_i(t) = \underbrace{\eta \cdot R_i(t)^{\alpha} \cdot H_i(t)^{\beta} - \delta_H \cdot H_i(t)}_{\text{indigenous innovation}} + \underbrace{\gamma_i(t) \cdot \left[R_i^T(t) + R_i^F(t) + R_i^D(t)\right]}_{\text{international technology diffusion}} \tag{4.25}$$

where accumulations of China's domestic knowledge stocks H_i are driven by two forces. 1) Indigenous innovation: Both indigenous R&D investment (R_i) and existing knowledge stock (H_i) contribute to direct creations of domestic knowledge. η denotes the efficiency of knowledge creation. δ_H is the depreciation rate of knowledge obsolescence. The conditions $0 < \eta < 1$, $0 < \alpha+\beta < 1$ implies diminishing returns to R&D in innovation (Rivera-Batiz and Romer, 1991; Popp, 2004; Bosetti et al., 2008); 2) International TD: Foreign knowledge diffusions occur through three channels: imports (R_i^T), FDI (R_i^F), and disembodied spillovers (R_i^D). China assimilates a fraction of the diffused knowledge according to local knowledge absorption capacity (γ_i).[35]

Note that, this *IPF* specification highlights three determinants of China's knowledge creation: (1) Indigenous R&D investment - the "no free lunch" assumption (to benefit from innovation, domestic countries should commit to undertake indigenous R&D and not solely free ride on foreign knowledge diffusion); (2) Existing stocks of knowledge - the "standing on the shoulders of predecessors" assumption (the more current stocks of knowledge, the more likely to create new knowledge); (3) International knowledge diffusion - the "pubic good sharing" assumption (domestic countries benefit from the positive externality of

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[34] At the initial period, the function takes a value of exp(-1)=0.367, since China has the largest difference in R&D intensity relative to the advanced countries. As time goes by, indigenous R&D improves China's R&D intensity with its level steadily reaching advanced country levels. As a result, the function value increases to its maximal level exp(0)=1. For a similar treatment, see van Meijl and van Tongeren (1999).

[35] International TD, corrected by local knowledge absorptive capacity, is a perfect substitute for domestic knowledge creation. Hence, indigenous innovation and international TD are additive in the specification of *IPF*.

international knowledge diffusion by absorbing foreign diffused knowledge).

4.3 Model Calibration and Implementation

4.3.1 Input-output Data and Knowledge Accounting

To implement the theoretical model in a numerical simulation, I construct a benchmark dataset for model calibration. First, the year 2004 IO tables are collected from the GTAP 7 Data Base (Narayanan and Walmsley, 2008). Second, we adapt the GTAP data to our model structure by aggregating the 113 world regions into 6, the 57 sectors into 12, and the 5 primary factors into labor and physical capital.[36] Finally, the 2004 IO tables are scaled to approximate each region's economy in the year 2005 (the base year of simulation) using 2005 growth rate of real GDP.

To calibrate China's domestic and foreign varieties of intermediate input and capital goods, we refer to the GTAP database (it distinguishes intersectoral transaction flows between domestic and import sources) to calibrate substitution between domestic and imported components of intermediate input commodities as well as regional composition of China's imports from foreign trading partners.[37] For investment capital goods, we refer to the *China Statistical Yearbook 2010* for the data on domestic and foreign components of fixed capital investment as well as regional composition of foreign-invested capital (FDI among foreign source countries) (NBS, 2011).[38]

The aforementioned steps produce a stylized IO dataset that can calibrate a traditional CGE model. However, this dataset is not well suited to calibrate a CGE model that incorporates a mechanism of endogenous TC (explicitly represented by knowledge), because it does not separately record the economic flows associated with R&D investment and knowledge input. To transform this stylized IO dataset, I need to collect sector-level R&D

[36] The original GTAP dataset records 113 world regions' economic IO flows associated with 57-by-57 sectors intermediate production transactions, 5 categories of primary factor inputs, and 4 components of final use. The FlexAgg program contained in the GTAP is used to perform data aggregation for model calibration.

[37] In explicit, industrial intermediate input purchases of domestic and imported goods at agent prices are contained in the GTAP data array "VDFA" and "VIFA". Regional details of bilateral trade flows are contained in the GTAP data array "VIWS".

[38] The GTAP dataset contains the sector-level data on physical capital investment, but not distinguishes domestic and foreign sources of such capital formations.

expenditure data from the OECD ANBERD database, and perform knowledge accounting to capture knowledge flows.[39] The procedure of knowledge accounting hereby constructs a modified IO dataset with an explicit representation of R&D investments and knowledge inputs, based on which the CGE model that features endogenous TC can be calibrated.

4.3.3 Parameterization and solver

The GEMPACK is used to solve the intertemporal optimization model.[40] The solver requires an initial equilibrium data as the benchmark point to calibrate the model. For an intertemporal dynamic model, this benchmark equilibrium data is required to record the values of economic variables at each time point over simulation periods, which is a time-series IO dataset (one for each time point) consistent with both intratemporal and intertemporal equations in the model.

To obtain such a full time-series dataset, we collect the available initial period (base year 2005) dataset and replicate it in future years over the period 2005-2030. Next, the Homotopy treatment is used to generate a non-steady-state baseline equilibrium dataset for model calibration.[41] Based on this consistent time-series benchmark dataset and the collected model parameters shown in Tabs. 4.1-4.2, the theoretical structure in the model can be numerically solved by the GEMPACK.

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[39] Knowledge accounting used in our study is building on the works of Terleckyj (1974), Scherer (1982), Sue Wing (2001; 2003), and Jin (2012), which used the IO-based knowledge flows matrices to measure inter-sectoral technology interactions in an economic system. For the details of R&D data preparation and knowledge accounting, see Appendix 4.B. For our model sectoral mapping by reference to the OECD ANBERD (ISIC Rev.3) sectoral classification, see Appendix 4.A.

[40] GEMPACK is a suite of general-purpose CGE modeling software, which is more efficient than GAMS to solve an intertemporal optimization model (Codsi et al., 1992; Harrison and Pearson, 1996; Horridge and Pearson, 2011). The GEMPACK TABLO codes for running the model are outlined in Appendix 4.C.

[41] Normally, the initial period is not in a steady-state (SS) equilibrium, the dataset created by replicating initial period data into future periods thus can't be used as a baseline to calibrate intertemporal equations (e.g., Eq., (4.3), Eq. (4.5)). To remedy this problem, I add a Homotopy term into each intertemporal equation and carry out a simulation where the Homotopy variables are shocked. This simulation then generates a non-SS time-series dataset that can be used a baseline to calibrate both intra- and inter-temporal equations in our model. The Homotopy treatment is automated by the TABLO program in GEMPACK. For the details, see Codsi et al. (1992), and Wendner (1999).

Table 4.1: Substitution elasticity

	σ^Q	σ^Z	σ^E	σ^M	σ^T	σ^{TT}	σ^F	σ^{FF}
Production sectors								
Electric utility	1.0	0.8	0.2	1.0	2.8	5.6	4.0	2.0
Gas utilities	1.0	0.8	0.9	0.2	2.8	5.6	4.0	2.0
Petro refining	1.0	0.5	0.2	0.2	2.1	4.2	4.0	2.0
Coal mining	1.0	1.7	0.2	0.5	3.0	6.1	4.0	2.0
Crude oil & gas	1.0	0.5	0.1	0.2	7.6	14.4	4.0	2.0
Mineral mining	1.0	1.0	1.1	2.8	0.9	1.8	4.0	2.0
Agriculture	1.0	1.3	0.6	1.7	2.4	4.8	4.0	2.0
Forestry	1.0	0.9	0.9	0.2	3.2	6.7	4.0	2.0
Durable	1.0	0.4	0.8	0.2	3.7	7.6	4.0	2.0
Non-durable	1.0	1.0	1.0	0.1	3.0	6.4	4.0	2.0
Transportation	1.0	0.5	0.2	0.2	1.9	3.8	4.0	2.0
Services	1.0	0.3	0.3	3.0	1.9	3.8	4.0	2.0

σ^Q: Elasticity of substitution between knowledge input and physical input composite.
σ^Z: Elasticity of substitution among the physical inputs of capital, labor, energy, and material.
σ^E: Elasticity of substitution among intermediate energy goods.
σ^M: Elasticity of substitution among intermediate material goods.
σ^T: Armington elasticity of substitution between domestic and imported variety of intermediate commodity.
σ^{TT}: CES elasticity of substitution for regional composition of import bundles.
σ^F: CES elasticity of substitution between domestic and foreign-invested physical capital goods.
σ^{FF}: CES elasticity of substitution for regional composition of FDI.

Note: Physical capital goods invested in individual sectors are assumed to have a substantial degree of homogeneity, I hereby impose a restriction that substitution elasticities of physical capital investment are equal across sectors. I also make assumptions that substitution elasticities within individual sectors are equal across world regions. However, this does not mean that the elasticities are the same across sectors within a world region.

Source: Goulder and Schneider (1999), McKibbin and Wilcoxen (1999), Sue Wing (2001; 2003), Löschel and Otto (2009), Narayanan and Walmsley (2008), Springer (1998), Mai (2005), Lejour et al. (2008).

Table 4.2: Parameter values

	CHN	USA	EUW	JPN	RIN	ROW
τ_Q	0.25	0.40	0.30	0.40	0.30	0.15
τ_I	0.20	0.12	0.15	0.20	0.15	0.20
τ_R	0.10	0.06	0.08	0.15	0.10	0.10
α	0.18	0.18	0.18	0.18	0.18	0.18
β	0.53	0.53	0.53	0.53	0.53	0.53
η	0.02	0.02	0.02	0.02	0.02	0.02
r	0.01	0.03	0.03	0.04	0.05	0.05
δ_K	0.05	0.05	0.05	0.05	0.05	0.05
δ_H	0.1	0.1	0.1	0.1	0.1	0.1
Ψ	4	4	4	4	4	4

τ_Q : Corporate profit tax rate

τ_I : Investment tax credit

τ_R : R&D tax credit

α : Elasticity of knowledge creation to R&D investment

β : Elasticity of knowledge creation to existing knowledge stock

η : Efficiency of knowledge creation

r : Real interest rate

δ_K : Depreciation rate of physical capital

δ_H : Depreciation rate of knowledge capital

Ψ : Investment adjustment cost coefficient

Source: Goulder and Schneider (1999), McKibbin and Wilcoxen (1999), Popp (2004), Bosetti et al. (2008), OECD (2010), World Bank (2011).

4.4 Results and Discussions

4.4.1 Alternative Scenario Settings

Recall that, I am motivated to examine the effect of indigenous R&D and foreign TD (the two sources of endogenous TC) on China's knowledge creation and carbon savings. To do that, I design and simulate two alternative scenarios: one is an endogenous TC scenario where indigenous R&D and foreign TD are explicitly considered, and the other is a reference scenario where indigenous R&D and foreign TD are ignored.[42]

In Section 4.4.2, I compare both scenarios to give insights into the effect of endogenous TC driven by indigenous R&D and foreign TD. In Section 4.4.3, I analyze the effect of policy interventions in a context of globalization, where economic and knowledge globalization policies are examined. By doing that, I capture two important effects of globalization (scale and technique effect) on domestic carbon saving. In Sections 4.4.4, I further examine whether domestic climate regulations can induce foreign knowledge inflows to help lower climate mitigation costs, from which the composition effect of globalization on domestic carbon savings can be considered.

4.4.2 Effects of Endogenous TC

For insights into the effect of endogenous TC, we compare economic and emission growth paths under the two aforementioned scenarios. As shown in Fig. 4.2(a), GDP in the reference scenario is projected to grow by 6.4% annually from $2327 to $10779 billion dollars between 2005 and 2030.[43] In contrast, GDP in the endogenous TC scenario rises from $2327 to $14272 billion dollars during the same period, creating an annual average growth rate of 7.6%. Consider that, the effect of endogenous TC stems from both indigenous R&D and foreign TD. To distinguish them, we simulate the growth path solely driven by indigenous R&D. Results show that with the stand-alone effort of indigenous R&D, GDP rises from $2327 to $13078

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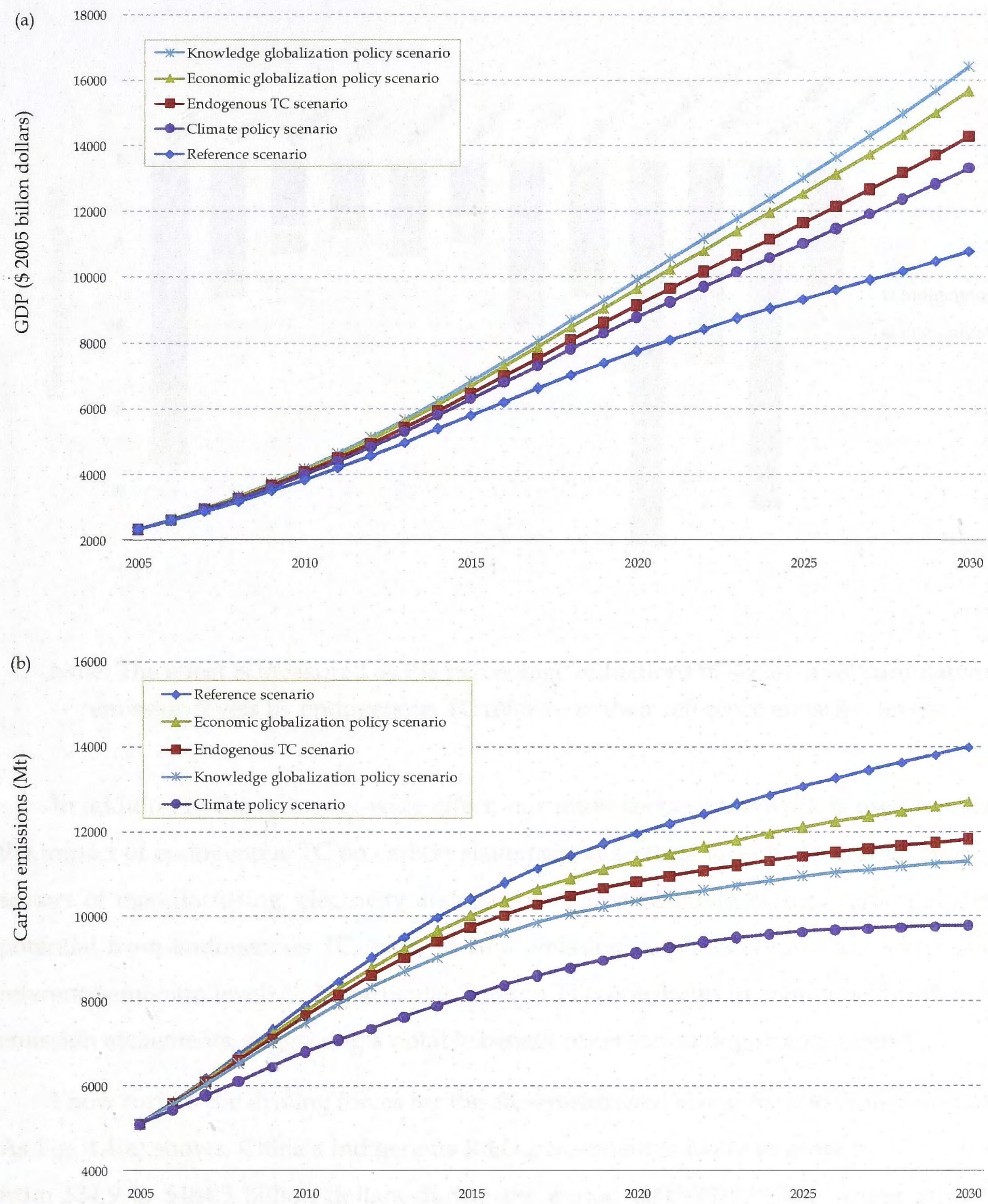
[42] In explicit, by setting indigenous R&D and foreign TD null, simulation in the reference scenario can drop the mechanism of endogenous TC, e.g., the process of knowledge creation as specified in Eq. (4.5).

[43] In our analysis, all measurements of output values are real GDP in unit of 2005 constant price U.S. dollars (year 2005 is the base period). To ensure the reliability of the model, we compare the simulated GDP and emissions growth rate with historical data, with their difference within an error range of 5%.

billion dollars between 2005-2030, generating an annual average growth rate of 7.2% that is lower than the rate achieved by the joint efforts of indigenous R&D and foreign TD (7.6%). This suggests that, on top of indigenous R&D, international TD contributes to an additional growth rate of 0.36% annually over the time period.

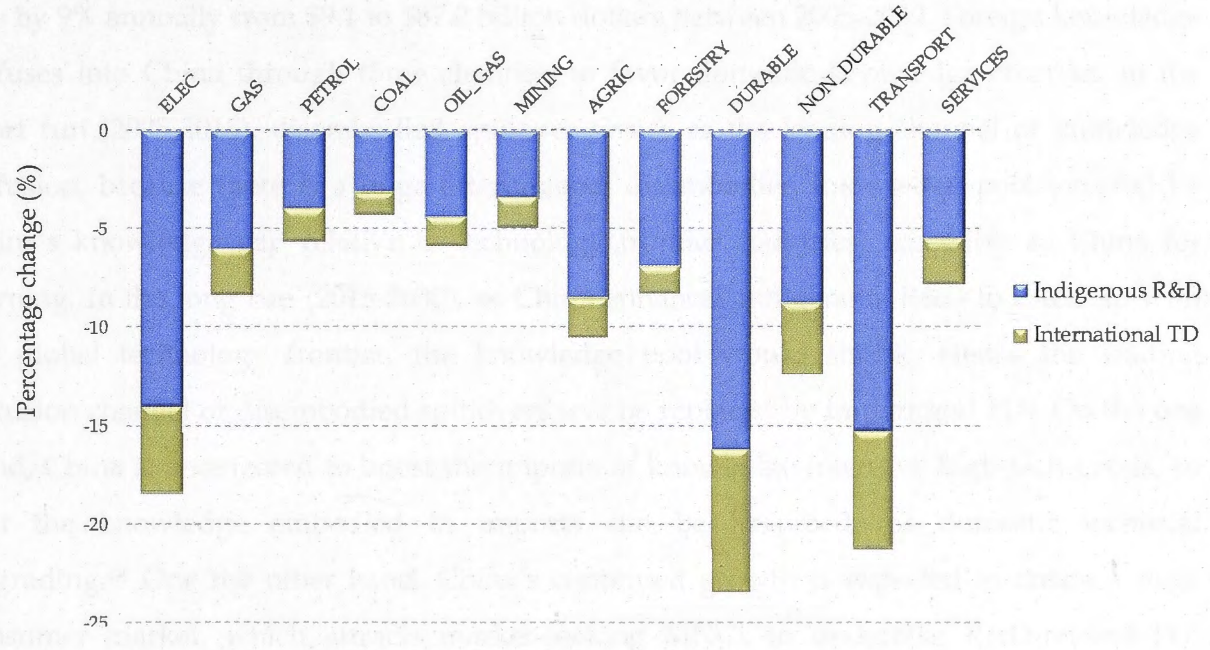
Climate repercussions of endogenous TC are shown in Fig. 4.2(b). Carbon emissions in the reference scenario are set to rapidly rise from 5100 to 13980 Mt between 2005-2030 - an average annual growth rate of 4.2%. In comparison, the endogenous TC scenario exhibits a trajectory of carbon emissions that grow by a lesser 3.5% annually from 5100 to 11817 Mt during the same period. As a result, cumulative emission cuts by endogenous TC relative to the reference levels are estimated to reach 24.8 gigatons over the time frame, of which indigenous R&D and international TD contribute to 18.3 and 6.5 gigatons emission cuts respectively. Measured in terms of percentage deviation, endogenous TC are seen to drive China's cumulative emissions below its reference levels by 9.1%, of which indigenous R&D and international TD contribute to 6.7% and 2.4% respectively. This suggests that foreign TD plays an important role to complement indigenous R&D in helping cut China's carbon emissions.

Figure 4.2: China's GDP and carbon emissions growth paths



Note:(a) China's GDP growth paths under alternative scenarios (reference, endogenous TC, economic globalization, knowledge globalization, climate policy); (b) China's CO_2 emissions growth paths under alternative scenarios (reference, endogenous TC, economic globalization, knowledge globalization, climate policy)

Figure 4.3: Effect of indigenous R&D investment and foreign technology diffusions (dual sources of endogenous TC) on carbon emission reductions



Note: The effect is measured as the percentage reductions of sector-level cumulative emission levels by endogenous TC relative to their reference emission levels.

In addition to the economy-wide effect, our multi-sector framework is used to examine the impact of endogenous TC on carbon abatement at sectoral level.[44] As Fig. 4.3 shows, the sectors of manufacturing, electricity and transport accommodate highest carbon abatement potential from endogenous TC, with 15-20% emission cuts relative to their sector-specific reference emission levels.[45] In particular, foreign TD contributes to about one fourth of these emission abatements, suggesting a notable benefit of carbon saving from foreign TD.

I now turn to the driving forces for the aforementioned economic and emission changes. As Fig. 4.4(a) shows, China's indigenous R&D investment is likely to grow by 12% annually from $34.9 to $484.3 billion dollars during the period 2005-2030.[46] The strong growths in

[44] This is done by firstly estimating sector-specific cumulative emission cuts by endogenous TC relative to the reference levels. Next, the cumulative emission cuts are decomposed into the abatement driven by indigenous R&D and international TD (the two sources of endogenous TC).
[45] The reason is that production technologies in these sectors heavily rely on the inputs of fossil fuels. Once indigenous R&D and foreign TD are induced to create new knowledge, these sectors have a large room of applying knowledge to substitute for fossil energy and save carbon.
[46] Accordingly, R&D intensity is estimated to rise from 1.5% to 3.2% as a share of GDP. This

R&D are spread across sectors, with manufacturing, agriculture, electric utility and transport investing the bulk of aggregate R&D.[47] In terms of international TD (the other source of endogenous TC), Fig. 4.4(b) shows that international knowledge diffusions are estimated to rise by 9% annually from $9.1 to $87.2 billion dollars between 2005-2030. Foreign knowledge diffuses into China through three channels to favor domestic knowledge creation. In the short run (2005-2015), disembodied spillover serves as the leading channel of knowledge diffusion, because there is a huge international disembodied knowledge pool (created by China's knowledge gap relative to technology frontier countries) accessible to China for learning. In the long run (2015-2030), as China enhances indigenous R&D to catch up with the global technology frontier, the knowledge pool would shrink. Hence the leading diffusion channel of disembodied spillovers will be replaced by import and FDI. On the one hand, China is anticipated to boost the imports of knowledge-intensive high-tech goods, so that the knowledge embodied in imports can be absorbed for domestic technical upgrading.[48] One the other hand, China's continued growth is expected to create a huge consumer market, which attracts market-seeking MNCs to undertake R&D-related FDI (particularly in R&D-intensive industries like pharmaceutical, electronic products, consumer durables) to develop customized products for local consumers. The pattern of R&D-related FDI hence accelerates the transfer of foreign advanced technology.[49]

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projection coincides with China's R&D blueprint in its transit towards an innovation-oriented economy - by 2020 the R&D intensity tends to reach 2.5% of the GDP (MOST, 2006).

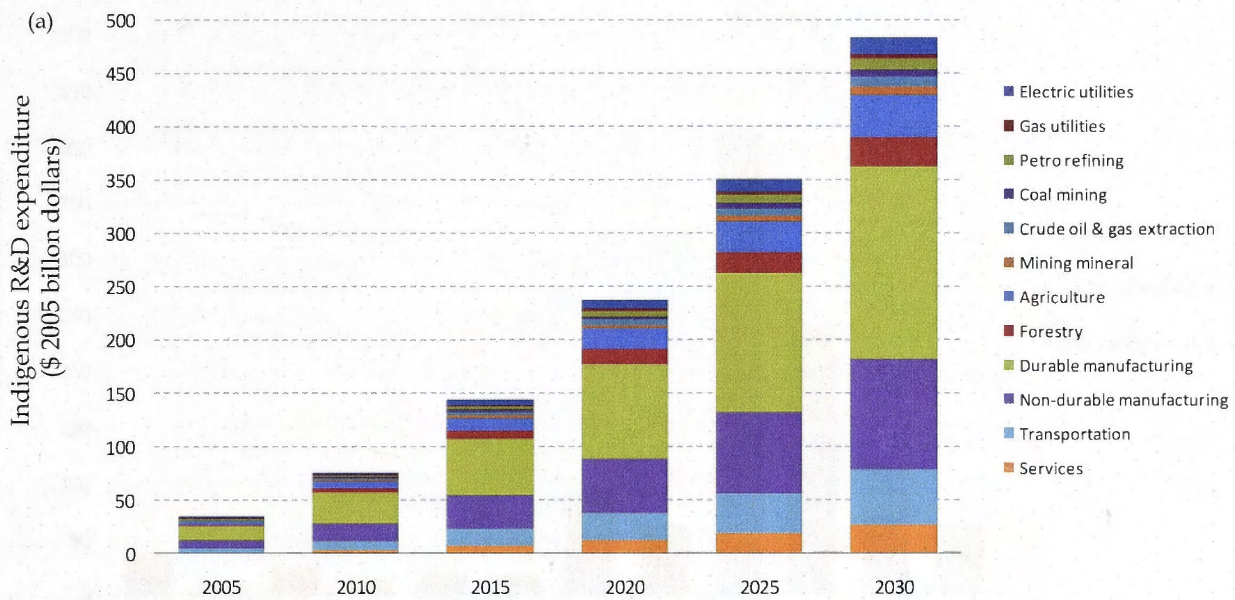
[47] The reason is that, R&D investments have higher marginal benefits in these sectors due to higher innovation efficiency and marginal products of knowledge application. Given the same marginal cost of R&D (the market price of R&D goods purchased), the sectors that accommodate higher marginal benefits would undertake more R&D investments. The results coincide with empirical evidence that about 80% of all R&D are concentrated in high-R&D industries producing chemical products, technology hardware and transport equipments (Keller, 2002; 2004).

[48] This technology acquisition strategy is reflected by China's recently announcement of boosting imports of hi-tech products, which gives priority to the imports of electronic and mechanical products that have gained growing shares (47%) in China's total imports portfolio (UNCTAD, 2010a). These imports are expected to foster China's emerging strategic industries, including biotechnology, nanotechnology, information technologies, and equipment manufacturing.

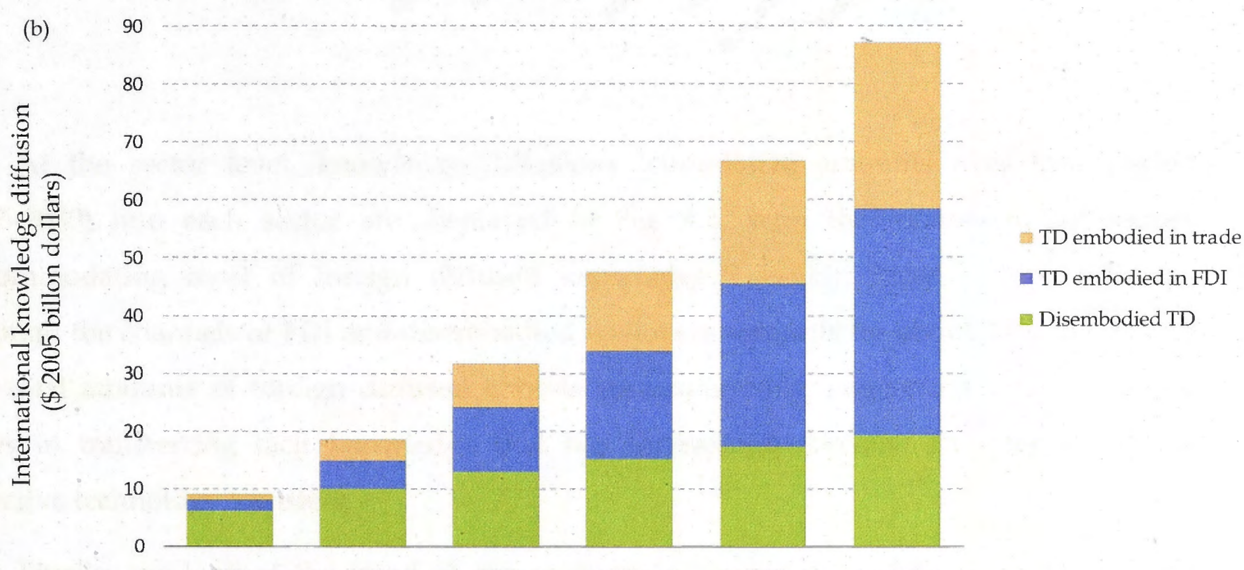
[49] R&D activities of MNCs are becoming increasingly internationalized, with the developing Asia continuing to be the most dynamic recipients. In the case of R&D expenditure by majority-owned foreign affiliates of U.S. MNCs, the share of developing Asian countries (particularly China) soared from 3% in 1994 to 15% in 2007. For example, the world's leading corporate R&D investors (e.g., Pfizer, Microsoft, Intel, IBM) have their own R&D centers in China (UNCTAD, 2005).

Figure 4.4: Intertemporal profiles of China's indigenous R&D investment and foreign knowledge inflows

(a)

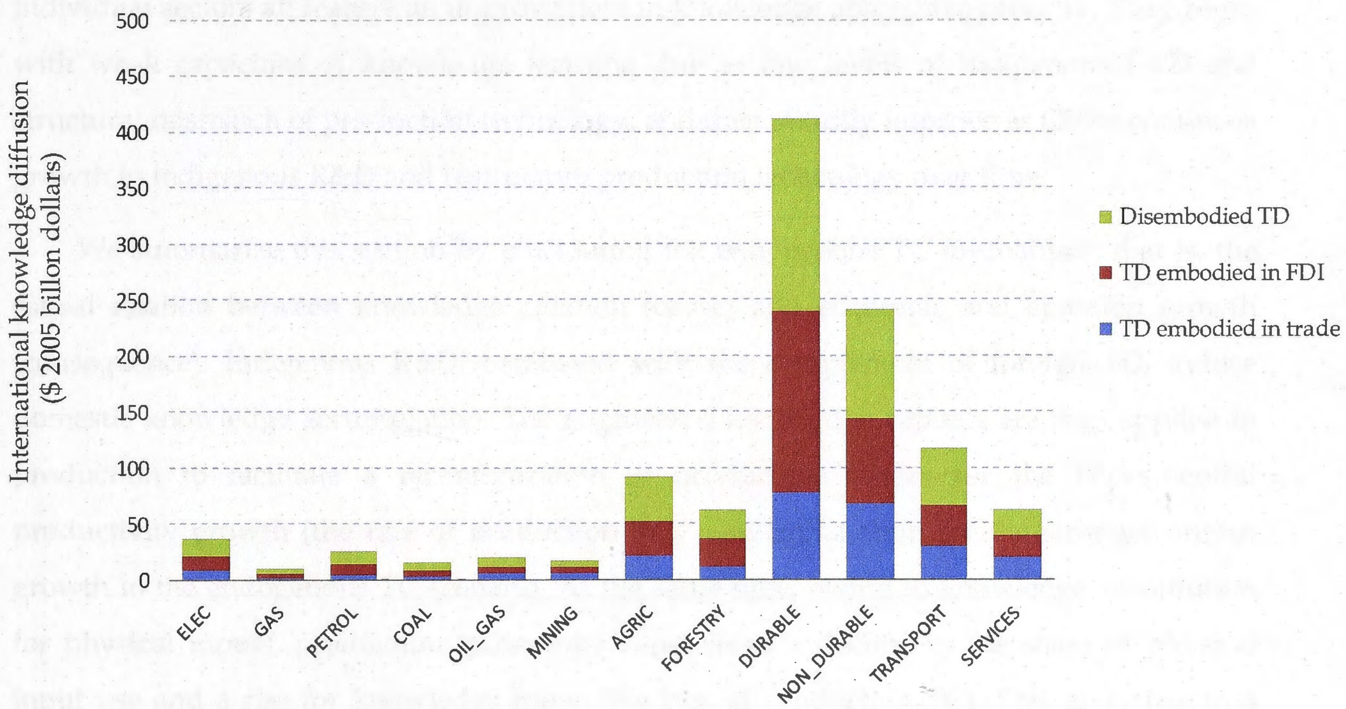


(b)



Note: (a) Intertemporal profiles of indigenous R&D investment and its sectoral composition; (b) Intertemporal profiles of international knowledge diffusion and the composition across three diffusion channels

Figure 4.5: Sector-specific international knowledge diffusion and the composition across three diffusion channels



At the sector level, knowledge diffusions (cumulative amounts over time period 2005-2030) into each sector are displayed in Fig. 4.5, with the manufacturing sectors accommodating most of foreign diffused knowledge.[50] Within these sectors, diffusion through the channels of FDI and disembodied spillovers accounts for about 35% and 40% of the total amounts of foreign diffused knowledge respectively, suggesting their important roles in transferring tacit knowledge that has increasingly become an integral part of effective technology transfers.

Finally, we look at the trend of convergence in cross-country R&D commitment. As shown in Fig. 4.6(a), global R&D spending is projected to triple over the time period, reaching an absolute level of $2.43 trillion dollars by 2030. This global picture, however, displays a shifting geography of R&D distribution. While foreign advanced countries like the

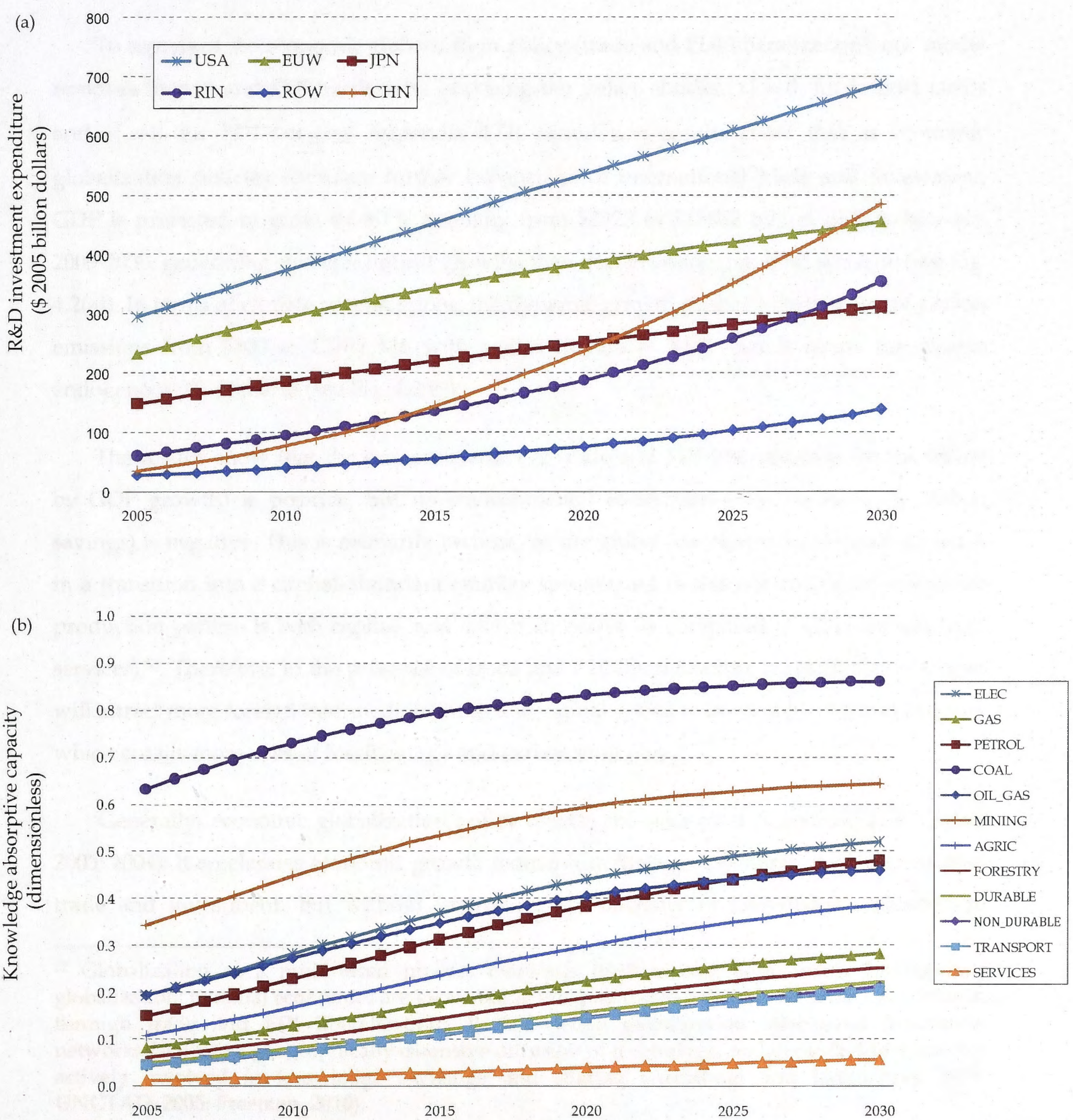
[50] This is because most of knowledge-intensive intermediate goods imports (e.g., electronic components) and foreign-installed capital goods (e.g., equipment) concentrate in China's manufacturing sectors, making foreign TD more likely to occur in this sector. Meanwhile, the stronger knowledge absorptive capacity (due to a higher level of R&D investment) in China's manufacturing sector facilitates absorbing foreign diffused knowledge.

U.S. and Japan contribute to most of total R&D investments, their shares are anticipated to decline which is largely offset by China's share gains. As a result, the continued convergence in cross-country R&D growth trend suggests China's technology catch-up and an improvement of knowledge absorptive capacity.[51] This is demonstrated in Fig. 4.6(b) where individual sectors all feature an improvement in knowledge absorptive capacity. They begin with weak capacities of knowledge learning due to low levels of indigenous R&D and structural mismatch of production technology, and then steadily improve as China continues growth in indigenous R&D and restructure production technology over time.

We summarize this section by elucidating the endogenous TC mechanism, that is, the causal relation between knowledge creation (cause) and economic and emission growth (consequence). Indigenous R&D, combined with the complement of foreign TD, induce domestic knowledge accumulation. The augmented knowledge capitals are then applied in production to facilitate a reconfiguration of production factors for the Hicks-neutral productivity growth (the rate of production TC) – an explanation for the stronger output growth in the endogenous TC scenario. At the same time, owing to knowledge substitution for physical inputs, production technology experiences a decline in the share of physical input use and a rise for knowledge input (the bias of production TC). This gives rise to a reduction in uses of fossil energy - an explanation for the lower emissions levels in the endogenous TC scenario.

[51] Recall that, as mentioned in Section 4.2.4.4, China's knowledge absorptive capacity is measured as the ratio of R&D investment between China and technologically advanced foreign countries.

Figure 4.6: (a) Intertemporal profiles of R&D investment expenditure across six world countries/regions; (b) Changin paths of China's knowledge absorptive capacity specific to individual production sector



4.4.3 Globalization Policy Scenario

As mentioned in Section 4.4.1, globalization may provide the benefit of low-carbon TD and carbon saving, we thus design globalization policy scenario in this section, where the effects of economic and knowledge globalization policies are explicitly considered.[52]

To represent the economic globalization policy (trade and FDI liberalization), our model removes import and FDI barriers by imposing the policy shocks: $\tau_i^T = 0$ for import tariffs and $\tau_I^F = 0$ for FDI tax (see Appendix 4.D). Simulation results show that as economic globalization policies stimulate further expansions of international trade and investment, GDP is projected to grow by 8.1% annually from \$2327 to \$15662 billion dollars between 2005-2030, generating stronger output growths than that in endogenous TC scenario (see Fig. 4.2(a)). In terms of climate repercussions, the dynamic growth pushes a further rise of carbon emissions from 5100 to 12705 Mt, with a growth rate of 3.8% that is above the rate in endogenous TC scenario (see Fig. 4.2(b)).

The results show that the economic effect of trade and FDI liberalization (as measured by GDP growth) is positive, but its environmental consequence (as measure by carbon savings) is negative. This is primarily because, as the global manufacturing engine, China is in a transition into a capital-abundant country specializing in manufacturing, of which the production pattern is both capital- and energy-intensive as compared to other sectors (e.g., services).[53] Therefore, in the presence of trade and FDI liberalization, manufacturing sectors will attract more foreign intermediate input and capital goods to expand production capacity, which entails more uses of fossil energy and carbon emission.

Generally, economic globalization policy creates the *scale effect* (Copeland and Taylor, 2003; 2004): It accelerates economic growth momentum through the stimulus of international trade and investment, but without improving the intensity of knowledge embodied in

[52] Globalization as a multi-faced process manifests itself in two basic ways. 1) Economic globalization: national economies are increasingly integrated into a globalized production system through trade and FDI liberalization; 2) Knowledge globalization: globalized innovation networks facilitate a geographically extensive diffusion of technology, making individual country actively involved in knowledge exchange and sharing (Archibugi and Iammarino, 1999; UNCTAD, 2005; Freeman, 2010).

[53] This coincides with the *"factor endowment hypothesis"*: there is a strong correlation between emissions and capital intensity, with globalization leading to emission increases in the capital-abundant countries (Antweiler et al. 2000; Cole and Elliot, 2003; Frankel, 2003).

import and FDI, this expanding production size necessarily requires more uses of fossil energy without carbon saving. Therefore, policies should be directly targeted at the growing globalization of knowledge to lift technology transfer restrictions erected by technologically advanced countries,[54] so that the intensity of knowledge embodied in foreign trade and investment can increase, creating the *technique effect* that favors domestic carbon savings.

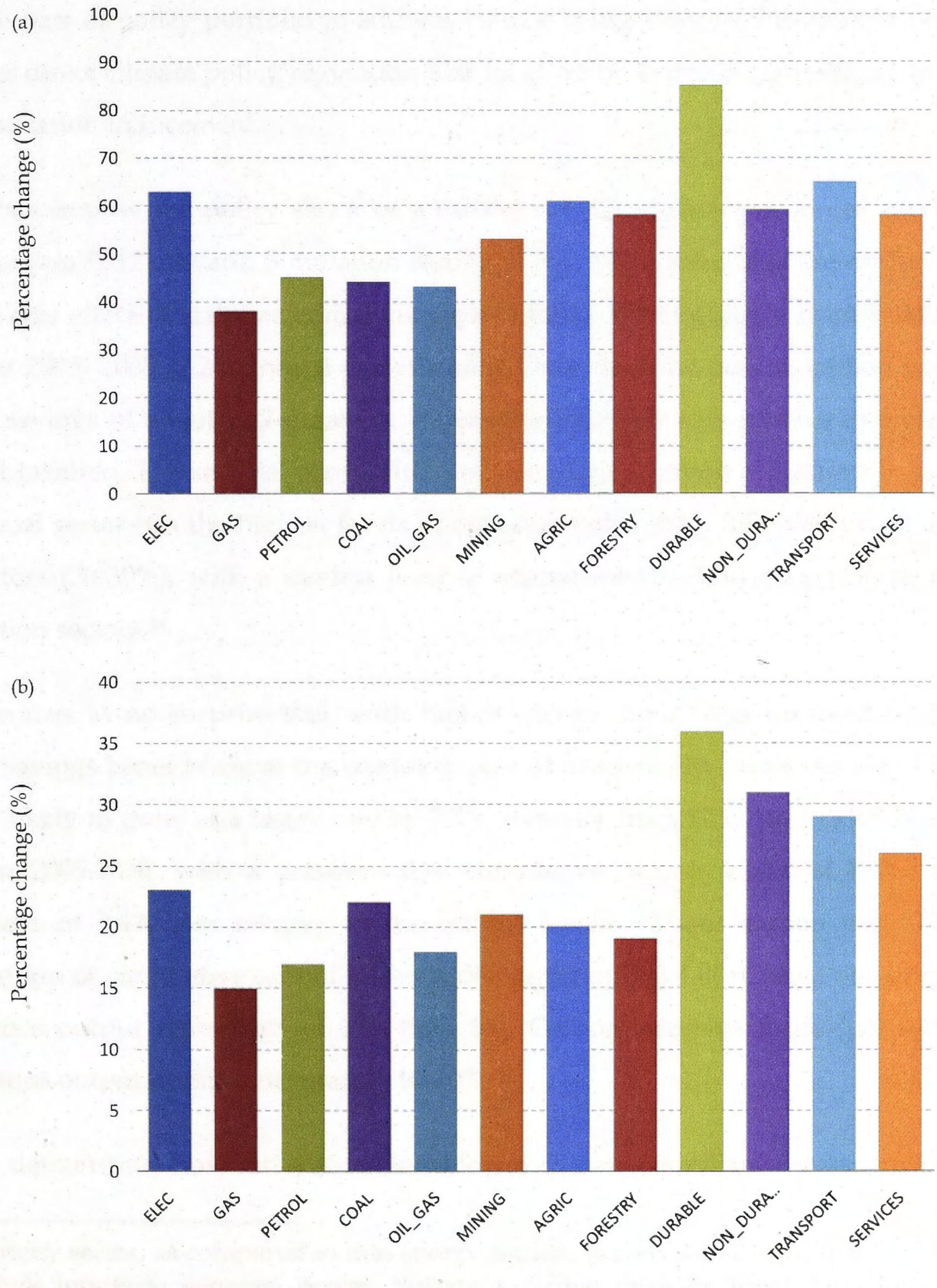
To represent the knowledge globalization policy, our model removes foreign barriers of TD by raising the values of parameters $\theta^T, \theta^F, \theta^D$ from 0.5 to 1. Results in Fig. 4.7 (a) show that, under a policy shock of knowledge globalization, sector-specific knowledge diffusions are induced to rise by a range of 50-80%, which facilitate the creation of more domestic knowledge. As a result, GDP is driven to grow by 8.2% annually from $2327 to $16404 billion dollars between 2005-2030 (see Fig. 4.2(a)). Meanwhile, augmented knowledge capital substitutes for the use of fossil energy, slowing down the emissions growth by 3.4% annually from 5100 to 11305 Mt between 2005-2030 (see Fig. 4.2(b)). Over the time frame, cumulative emission cuts reach a level of 15.8 gigatons, which suggests that knowledge globalization policy can a *technique effect* that favors domestic carbon saving (Copeland and Taylor, 2003; 2004).

Meanwhile, once removing foreign barriers of TD, China's indigenous R&D are induced to increase by a range of 20-35% across sectors (see Fig. 4.7(b)), suggesting that foreign TD in knowledge globalization does not necessarily crowd out indigenous R&D. There is little evidence on the incentive of free riding on foreign knowledge diffusion without indigenous R&D commitment. That's because indigenous R&D investment is necessary for the recipient country China to build indigenous capacity of absorbing foreign diffused knowledge.

In summary, economic globalization policy (trade and FDI liberalization) facilitates a transition to economic integration and production growth, but leading to higher emissions levels without carbon saving (*scale effect*). To acquire the benefits of domestic carbon saving, knowledge globalization policy should be implemented to create the *technique effect*, which depends on: 1) Removal of TD restrictions by technologically advanced nations; and 2) Improvement of knowledge absorptive capacity by the host developing countries.

[54] While removal of import tariff and FDI tax reflects economic globalization policy adopted by China (technology demand side) to grant foreign access to domestic market for technology transfer, a lifting of knowledge transfer limits by foreign advanced countries (technology supply side) can be thought of as a particular type of knowledge globalization policy (UNCTAD, 2010b).

Figure 4.7: Effect of knowledge globalization policy to induce foreign knowledge inflows and indigenous R&D for knowledge absorption



Note: (a) Effect of knowledge globalization policy on foreign technology diffusion is measured as percentage changes of foreign knowledge inflows induced by the policy shock relative to knowledge inflows without that policy shock; (b) Effect of knowledge globalization policy on indigenous R&D is measured as percentage changes of R&D investment induced by the policy shock relative to the knowledge inflows without that policy shock

4.4.4 Climate Policy Scenario

In the last section, knowledge globalization, by facilitating foreign technology flows, indirectly favors domestic carbon savings. While important, it can't stand alone, but rather must be part of policy portfolio to address climate mitigation. In this section, we explicitly consider direct climate policy regulation and its effect on economic growth, carbon savings, and innovation inducement.

I thus impose the policy shock of a carbon tax, $20 dollars per ton of carbon dioxide from the year 2012 onward. Simulation results in Fig. 4.2(b) show that the carbon tax creates a noticeable effect to stabilize emissions growth trend, driving down from 5100 to 9795 Mt between 2005- 2030 (2.2% annual growth rate). Over the time period, carbon tax generates carbon savings of about 26.7 gigatons, translating into 12% cuts relative to emission levels without taxation. The sectoral composition of cumulative carbon abatement is given in Fig. 4.8(a), coal sector has the highest levels of emission cuts (50%), followed by oil and natural gas sectors (20-30%), with a modest level of abatement (10-20%) occurring in non-energy production sectors.[55]

It comes as no surprise that, with higher energy input costs imposed by carbon tax, carbon savings benefits are at the economic cost of deadweight losses. As Fig. 4.2(a) shows, GDP is likely to grow at a lesser rate by 7.2% annually from $2327 to $13309 billion dollars between 2005-2030, with a present-value cumulative output losses of $9763 billion (an equivalent of 2.4% loss relative to the output levels without carbon tax). The sectoral composition of cumulative output losses is displayed in Fig. 4.8(b). Most non-energy sectors experience output reductions of less than 5%. Carbon-intensive fossil fuel sectors suffer precipitous output declines of roughly 10-20%.[56]

To demonstrate how innovation helps lower climate compliance costs, we simulate the

[55] Electricity sector, as compared to non-energy sectors, is carbon-intensive that heavily relies on fossil fuels inputs to generate power. Putting a carbon price on fossil fuels thus incentivize electricity sector to lower fossil fuels uses, hence having a proportionally higher level in carbon emissions cuts.

[56] As compared to primary energy sectors (coal, natural gas, oil), electricity sector (secondary energy sector) is R&D-intensive. Carbon taxation thus induces electricity sector to create and apply low-carbon energy technologies (e.g., wind, solar) to generate power, which partially offsets output loss of coal-fired electricity incurred by carbon tax. Hence, electricity sector has a proportionally lower level of output losses.

deadweight loss incurred by carbon taxation in the reference (no-innovation) scenario, where endogenous-TC is absent in private firms' response to energy price shock. Results show that carbon tax is likely to drive down GDP growth at a lesser rate (5.8% annually) from $2327 to $9357 billion dollars between 2005-2030, with a present-value cumulative output losses of $23410 billion dollars. It implies that endogenous TC helps partially mitigate economic costs of $13647 (23410-9763) billion dollars, of which foreign TD (one source of endogenous TC) helps mitigate a deadweight loss of $3713 billion dollars. Therefore, while climate regulation has a negative effect on economic production, the innovative response of private firm can help partially mitigate the climate compliance costs.

For insights into the effect of climate policy on innovation inducement, we examine the effect of the carbon tax on the R&D intensity at sector level. As Fig. 4.8 (c) shows, although higher input cost incurred by carbon tax would diminish the absolute levels of production output and hence indigenous R&D spending, R&D intensity (R&D to output ratio) does not necessarily drop across sectors. Decline in cumulative R&D exceeds the fall in cumulative outputs in fossil fuel sectors, but falls short of those in non-fossil fuel sectors. Consequently, R&D intensity increases slightly across a range of non-fossil fuel sectors, suggesting that indigenous R&D investments are induced by climate policy in these sectors.

Moreover, as Fig. 4.8(d) shows, the decline in cumulative foreign TD also exceeds the fall in cumulative outputs in fossil fuel sectors, but falls short of those in non-fossil fuel sectors. As a result, input share of foreign diffused knowledge in domestic production increase slightly across non-fossil fuel sectors, which indicates that domestic climate regulations also stimulate external knowledge inflows to help increase knowledge uses in domestic production technology.[57] This finding thus broadens the scope of *"Porter Hypothesis"* within a close economy, in the sense that a tightening of domestic climate regulation also stimulates inflows of external knowledge that helps increase knowledge

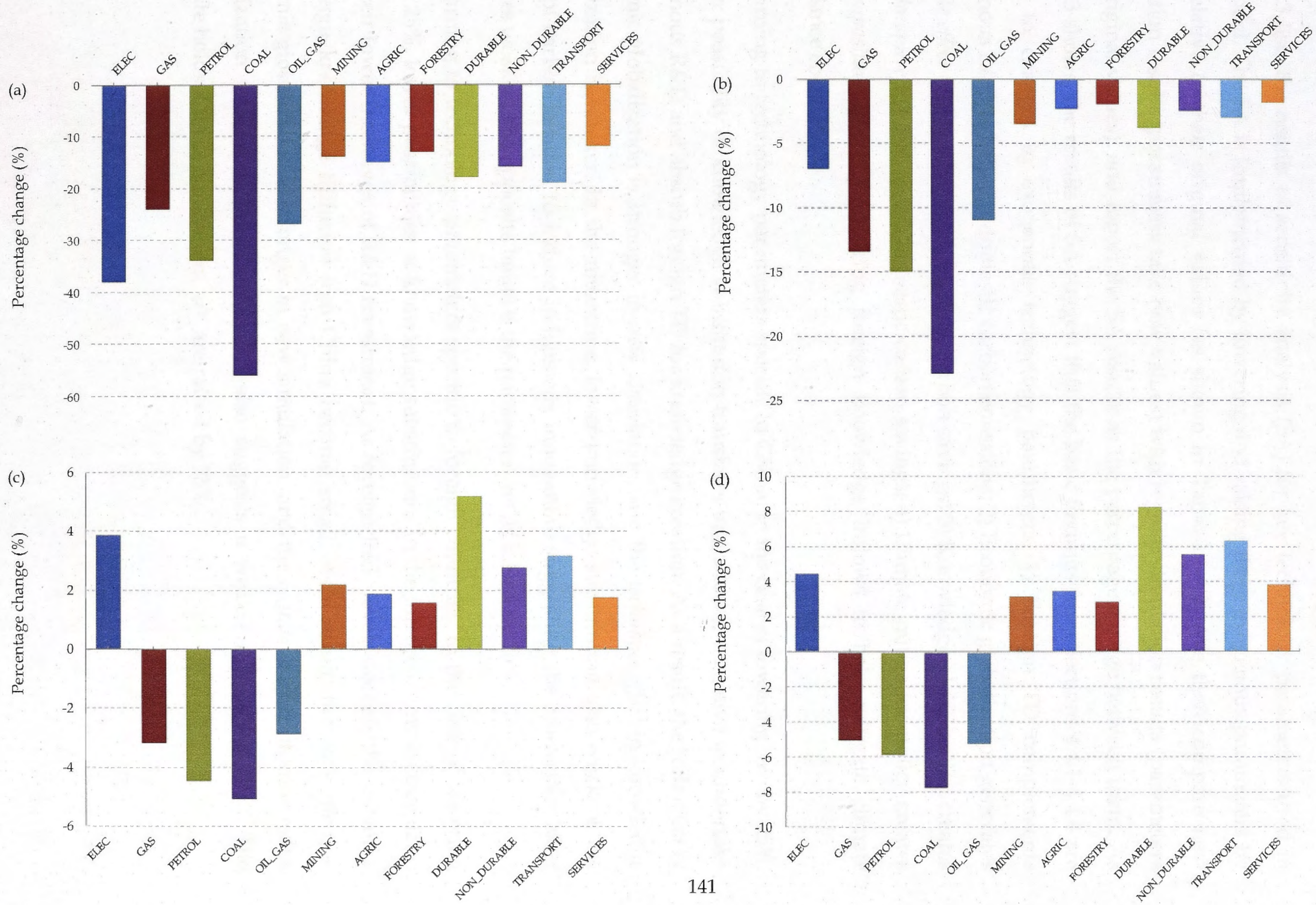
[57] This can be explained from a technology push/market pull perspective. Foreign developed countries have the "first mover advantage" in selling low-carbon technologies to the latecomers (technology push). Meanwhile, China's climate policies create a carbon market where huge demands for low-carbon products and technologies can draw in market-seeking foreign investors and innovators (market pull). Moreover, transfers of climate-friendly technology can lower the climate compliance cost in the recipient developing countries, making climate regulations more likely (Lovely and Popp, 2011; Popp, 2011).

intensity in domestic production technology.[58]

In summary, under stringent climate regulation, individual sectors are induced to create new knowledge through indigenous R&D investment and foreign knowledge inflows. From an economy-wide perspective, once new knowledge is applied in domestic economic system, the contribution of knowledge-intensive sectors would expand, with that of carbon-intensive sectors contracting. Therefore, such a shift in the composition/structure of the aggregate economy suggests a *composition effect*.

[58] *"Porter Hypothesis"* holds that stringent environmental regulations not only create direct environmental benefits but also have indirect benefit of stimulating technological innovation (Porter and van der Linde, 1995). For empirical evidences of the induced innovation hypothesis, see Newell et al. (1999), Popp (2002). For numerical simulation analysis, see Goulder and Schneider (1999), Sue Wing (2003) and Jin (2012).

Figure 4.8: (a) Effect of carbon tax on sector-level cumulative emission cuts; (b) Effect of carbon tax on sector-level cumulative production output losses; (c) Effect of carbon tax on sector-level R&D intensity; (d) Effect of carbon tax on sector-level input share of foreign diffused knowledge in domestic production.



4.4.5 Sensitivity Analysis

Tab. 4.3 lists the results of sensitivity analysis (SA) for key technology parameters used in our model. The SA is implemented by lowering and raising these exogenous parameters by 25% relative to their original values (as shown in Tabs. 4.1-4.2). We then compare new simulation results (parameters take new values) with regular simulation results (parameters take original values), and report the SA results as the percentage change between them. As Tab. 4.3 shows, the results of SA suggest that the basic findings from Sections 4.4.1-4.4.4 are robust to changes in exogenous technology parameters. 1) Foreign TD complements indigenous R&D to help cut domestic carbon emissions; 2) Economic globalization generates the *scale effect* that is adverse to domestic carbon savings; 3) Knowledge globalization creates the *technique effect* that favors domestic carbon savings; 4) Climate mitigation policy creates the *composition effect* by inducing foreign knowledge inflows to help mitigate climate compliance costs.

Turning to technology parameters specific to China, in the case of lowering σ^Q by 25%, a lower possibility of knowledge substitution translates into a lower incentive to undertake indigenous R&D and absorb foreign TD for knowledge creation. As a result, the *scale effect* of economic globalization is stronger in new simulation, and the *technique effect* in knowledge globalization is weaker. In the meantime, lower knowledge substitution also weakens the effect of carbon taxation to induce indigenous innovation, suggesting the *composition effect* becomes weaker. The opposite holds if the parameter σ^Q is raised by 25%.

Turning to technology parameters specific to foreign countries, in the case of lowering σ^Q by 25%, lower possibilities of knowledge substitutions in the foreign countries translates into their lower incentives of R&D investment. As foreign R&D levels decline, the potential of foreign knowledge diffusion into China become small. As a result, the *scale effect* of economic globalization is stronger in new simulation, and the *technique effect* of knowledge globalization is weaker. Less foreign TD also suggests a weaker *composition effect*. The opposite holds if these parameters σ^Q are raised by 25%.

Table 4.3: Results of sensitivity analysis

		Endogenous TC [a]		Emission cuts [b]		Scale effect [c]	Technique effect [d]	Composition effect		
		Indigenous R&D	Foreign TD	Indigenous R&D	Foreign TD			R&D intensity [e]	Share of foreign knowledge [f]	Cost savings [g]
China										
σ^Q	Low[h]	-3.52%	-2.61%	6.47%	2.33%	3.85%	2.23%	-2.84%	-0.57%	-1.02%
	High	3.64%	2.85%	6.92%	2.46%	-3.47%	-2.08%	2.65%	0.48%	0.93%
δ_H	Low	2.76%	2.53%	6.89%	2.46%	-2.12%	-0.87%	1.72%	0.36%	0.64%
	High	-2.48%	-2.15%	6.51%	2.34%	1.86%	0.74%	-1.96%	-0.33%	-0.76%
α, β, η	Low	-5.46%	-4.27%	6.35%	2.29%	6.12%	5.20%	-4.15%	-0.91%	-1.45%
	High	6.27%	4.89%	7.12%	2.51%	-5.46%	-4.70%	3.72%	0.64%	1.53%
Foreign										
σ^Q	Low	-1.26%	-3.85%	6.62%	2.26%	1.58%	1.07%	-0.98%	-3.76%	-0.56%
	High	1.15%	3.67%	6.77%	2.53%	-1.46%	-0.95%	1.11%	3.82%	0.46%
δ_H	Low	0.75%	2.28%	6.76%	2.49%	-0.91%	-0.43%	0.66%	2.34%	0.30%
	High	-0.93%	-2.57%	6.64%	2.31%	0.82%	0.37%	-0.57%	-2.19%	-0.24%
α, β, η	Low	-1.39%	-5.72%	6.62%	2.22%	2.51%	2.13%	-1.72%	-5.92%	-0.95%
	High	1.12%	5.48%	6.79%	2.58%	-2.46%	-2.04%	1.78%	5.75%	0.69%

σ^Q: Elasticity of substitution between knowledge and physical input. δ_H: Depreciation rate of knowledge capital stock
α: Elasticity of knowledge creation to R&D. β: Elasticity of knowledge creation to existing knowledge stock. η: Efficiency of knowledge creation

[a] Percentage change of China's cumulative indigenous R&D and cumulative international TD in new simulation relative to that in regular simulation.

[b] China's cumulative emission cuts driven by indigenous R&D and international TD in new simulations. (in regular simulation, cumulative emission cuts driven by indigenous R&D and international TD equal to 6.7% and 2.4%, respectively)

[c] Percentage change of China's cumulative carbon emissions in economic globalization scenario in new simulation relative to that in regular simulation.

[d] Percentage change of China's cumulative carbon emissions in knowledge globalization scenario in new simulation relative to that in regular simulation..

[e] Percentage change of the average levels (among China's eight non-fossil fuel sectors) of R&D intensity (ratio of indigenous R&D investment to output) in new simulation relative to that in regular simulation.

[f] Percentage change of the average levels (among China's eight non-fossil fuel sectors) of the input share of foreign diffused knowledge (ratio of foreign diffused knowledge to output) in new simulation relative to that in regular simulation.

[g] Percentage change of China's climate compliance cost savings (mitigation of the deadweight losses incurred by carbon tax) by endogenous TC in new simulation relative to that in regular simulation.

[h] Low and High refer to lowering and raising exogenous parameters by 25% relative to their central case values, respectively.

4.5 Conclusion and Outlook

Building on a multi-region global numerical model, this chapter considers both indigenous R&D and foreign TD as dual sources of endogenous TC for domestic carbon savings. The model fully represents international TD through three diffusion channels of trade, FDI, and disembodied spillovers, with an elaborate treatment of knowledge absorptive capacity.

Simulation results show that 1) foreign TD contributes to 20%-25% of carbon emission cuts by endogenous TC. In the short run, 60-70% of foreign knowledge diffusion occurs via the channel of disembodied spillover. In the long run, the leading diffusion channels become embodied knowledge diffusion via import and FDI which account for almost 80% of total foreign TD; 2) Trade and FDI liberalization facilitates economic growth, creating an additional GDP growth rate of about 0.5% annually over time. But this is at the cost of more carbon emissions, raising emissions growth rate by about 0.3% annually. So economic globalization policy may not create the benefit of domestic carbon saving (*scale effect*); 3) Removal of foreign technology transfers barriers facilitates domestic knowledge creation and productivity growth, generating an additional GDP growth rate of about 0.1% annually. It also brings down the carbon emission growth rate of roughly 0.4% annually. So knowledge globalization policy creates the benefit of domestic carbon savings (*technique effect*); 4) Domestic climate policies induce both indigenous R&D (R&D intensity increases by about 2-5%) and foreign TD (input share of foreign diffused knowledge rise by about 5-8%). As a result, both types of innovation inducement would help shift the composition of domestic production techniques (*composition effect*), which eventually lowers climate compliance cost (output losses incurred by carbon taxation) by about 15-20%.

Needless to say, a number of model extensions are required in future work. In particular, current works focus on modeling unidirectional knowledge diffusion from technologically advanced countries to China, without factoring into multidirectional technology interaction. As China is increasingly integrated into the global innovation landscape, it is possible for technology incumbents in advanced countries to learn the ideas created by the new entrants in the emerging markets. Hence, future work should study the mechanism of cross-country multidirectional knowledge diffusions, based on which the issue of international technology coordination can be addressed.

Appendix to Chapter 4

4.A Country Composition of Regions

Region Number	Region Name	Region Description
1	CHN	China
2	USA	United States of America
3	JPN	Japan
4	EUW	Western Europe
5	RIN	Rest of the Industrialized Countries
6	ROW	Rest of the World

Western Europe:

Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom

Rest of the Industrialized Countries:

Canada, Australia, New Zealand, Korea, Singapore, Hong Kong, Taiwan

Rest of the World:

All countries not included in other region groups

Model sectoral classification and mapping

Sector number/name in our mode	GTAP sector numbers	OECD ANBERD sector number
1. Electric utilities	43	40
2. Gas utilities	44	41
3. Petroleum refining	32	23
4. Coal mining	15	10
5. Crude oil & gas extraction	16-17	11
6. Mineral mining	18	12-14
7. Agriculture	01-12, 14	01, 03-05
8. Forestry & wood products	13, 30	02, 20
9. Durable manufacturing	34-42	26-37
10. Nondurable manufacturing	19-29, 31, 33	15-19, 21-22, 24-25
11. Transportation	48-50	60-64
12. Services	45-47, 51-57	45, 50-59, 70-99

4.B Knowledge Accounting

In the *System of National Accounts*, the conventional IO table treats corporate expenditures on R&D as current cost of production along with intermediate inputs, implying that only a portion of each intermediate transaction reflects the value of pure physical flows, with the remainder being the value of intangible knowledge flows embodied in that transaction. In line with this principle, knowledge accounting can be conceptualized as follows: in a stylized IO table, the intangible knowledge flows matrix $\boldsymbol{\Omega}=[\omega_{ji}]_{j=1,\dots,n;i=1,\dots,n}$ is embodied in the intermediate transactions matrix $\mathbf{X}=[x_{ji}]_{j=1,\dots,n;i=1,\dots,n}$. The row sums of $\boldsymbol{\Omega}$ is the sector-specific R&D investments, $R_j=\sum_i \omega_{ji}$, and the column sums of $\boldsymbol{\Omega}$ denote the remuneration of knowledge capital as primary factor inputs into production, $H_i=\sum_j \omega_{ji}$.

Based on the embodied technology hypothesis, we estimate the intangible knowledge flows embodied in the intermediate transaction as:

$$\underbrace{\frac{\omega_{j1}}{x_{j1}}=\dots=\frac{\omega_{ji}}{x_{ji}}=\dots=\frac{\omega_{jn}}{x_{jn}}}_{\text{Embodied technology hypothesis}}=\frac{\sum_i \omega_{ji}}{\sum_i x_{ji}}=\frac{R_j}{X_j} \quad \Rightarrow \quad \omega_{ji}=\frac{x_{ji}}{X_j}\cdot R_j \tag{4.B.1}$$

where x_{ji} is the (j,i) cell of the intermediate transaction matrix $\mathbf{X}$ in the stylized IO table, representing the intersectoral transaction of intermediate inputs from sector j to i. ω_{ji} is the intangible knowledge flows embodied in that transaction. R_j, X_j denote R&D investment and intermediate production specific to sector j, respectively. The embodied technology hypothesis claims that, for any given commodity j, the knowledge embodiment ratio ω_{ji}/x_{ji} is invariant across sectors in intermediate production.

As mentioned previously, innovations in foreign technologically advanced countries are driven by their indigenous R&D, but TC in China benefits from both indigenous R&D and international knowledge diffusions. Hence, a distinction is made in knowledge accounting between foreign technologically advanced economies and China. For the former, sector-specific R&D investment (R_j) is equal to indigenous R&D expenditure, of which the sector-level data can be collected form OECD ANBERD dataset. China's R&D investment, in comparison, amounts to a sum of indigenous R&D and international knowledge diffusion.

China's indigenous R&D expenditure data is also available from OECD ANBERD dataset. International knowledge diffusions through the three channels (trade, FDI and disembodied spillovers) are calculated using the formula presented in the manuscript Sections 2.4.1-2.4.3. The shares of product sales to other sectors in intermediate transaction (x_{ji}/X_j) are calculated from the stylized IO table. We then use Eq. (4.B.1) to estimate the intangible knowledge flows embodied in the intermediate production.

Generally, the knowledge accounting by using Eq. (4.B.1) is equivalent to a horizontal mapping of the column of sector-specific R&D investment expenditure into each cell in the intangible knowledge flow matrix. Then, the knowledge flow matrix is vertically aggregated to create an additional row of knowledge input in the primary factor use matrix $\mathbf{V}$, with each element being the value of knowledge input into production sector i, $H_i = \sum_j \omega_{ji}$. Finally, the elements of intermediate production matrix $\tilde{\mathbf{X}}$ are purged of the intangible knowledge flows to represent the value of pure physical flows.

The residual elements of intermediate transaction matrix ($\tilde{x}_{ji} = x_{ji} - \omega_{ji}$) is subject to the non-negativity constraint. Once the column and row balance hold in the stylized IO table, the matrix balance still holds for the modified IO table with explicit knowledge accounting: $\sum_j \tilde{x}_{jk} + \sum_f v_{fk} + v_{Hk} = \sum_i \tilde{x}_{ki} + \sum_f \tilde{g}_{kf} + g_{kR}$. This procedure hereby constructs a modified IO dataset with an explicit representation of R&D investments and knowledge inputs, based on which the CGE model with endogenous TC can be calibrated.

4.C GEMPACK TABLO Model Codes

The model developed in Chapter 4 focus on representing unidirectional R&D spillovers from foreign countries to China. The modeling structure of each foreign country (e.g., USA, JPN, EUW, RIN, ROW) is similar to a single-country CGE framework incorporating indigenous R&D (see Appendix 3.C in Chapter 3). Meanwhile, innovations in China can benefit from knowledge diffusion from these foreign countries, with TC depending on both indigenous R&D and international TD. So the basic structure of the China part is similar to Appendix 3.C in Chapter 3, with an extension that characterizes foreign knowledge diffusion into China as outlined in the following GEMPACK TABLO code.

```
!==========================================================================================
GEMPACK TABLO code for implementing the model of foreign knowledge diffusion into China
==========================================================================================!
!=============================================
SETS
=============================================!
SET sectors # 12 production sectors #
(a01, a02, a03, a04, a05, a06, a07, a08, a09, a10, a11, a12);
SET sectors_e # 5 energy sectors #
(a01, a02, a03, a04, a05);
SET sectors_m # 7 material sectors #
(a06, a07, a08, a09, a10, a11, a12);
SUBSET sectors_e IS SUBSET OF sectors;
SUBSET sectors_m IS SUBSET OF sectors;

SET goods # 12 commodities #
(g01, g02, g03, g04, g05, g06, g07, g08, g09, g10, g11, g12);
SET goods_e # 5 energy commodities #
(g01, g02, g03, g04, g05);
SET goods_m # 7 material commodities #
(g06, g07, g08, g09, g10, g11, g12);
SUBSET goods_e IS SUBSET OF goods;
SUBSET goods_m IS SUBSET OF goods;

SET regions # 4 foreign regions #
(USA, EUW, JPN, RIN, ROW);

SET
(INTERTEMPORAL) alltime # all time periods #          (p0 - p25);
SET
(INTERTEMPORAL) fwdtime # domain of forward difference #  (p0 - p24);
SET
(INTERTEMPORAL) endtime # ending time #               (p25);
SUBSET fwdtime IS SUBSET OF alltime;
SUBSET endtime IS SUBSET OF alltime;

!=======================================================
Definition of coefficients and variable associated with
Representing China R&D and knowledge capital accumulation
=======================================================!
Coefficient
(parameter)                                          CAH
# knowledge creation efficiency in IPF #;
(parameter)                                          CALPHA
# power on R in IPF #;
(parameter)                                          CBETA
# power on H in IPF #;
(parameter)                                          CDELTAH
```

```
# knowledge depreciation rate #;
(all, t, alltime)                                              CTRTC(t)
# R&D tax credit #;
(all, i, sectors) (all, t, alltime)                            LCRNV(i,t)
# R&D investment in knowledge capital #;
(all, t, alltime)                                              LCPRRR(t)
# purchase price of raw R&D good #;
(all, i, sectors) (all, t, alltime)                            LCHCP(i,t)
# knowledge capital stock #;
(all, i, sectors) (all, t, alltime)                            LCLAMR(i,t)
# shadow price of knowledge capital#;
                                                               BARD
# Foreign barrier to disembodied R&D spillover #;
(all,i,sectors)(all,t,alltime)                                 LRNV_R(i,t)
# total R&D of technology frontier countries #;
 (all,i,sectors)(all,t,alltime)                                LRTD(i,t)
# disembodied R&D spillover #;

Read
CAH  from file BASEDATA header "CAH";
CALPHA  from file BASEDATA header "CALP";
CBETA  from file BASEDATA header "CBET";
CDELTAH  from file BASEDATA header "CDEH";
CTRTC  from file BASEDATA header "CTRT";
LCHCP  from file BASEDATA header "CHCP";
LCRNV  from file BASEDATA header "CRNV";
LCPRRR  from file BASEDATA header "CPRR";
BARD from FILE BASEDATA header "BARD";

Formula
(all,i,sectors)(all,t,alltime)
LRNV_R(i,t) = sum{r, regions, LRNV(r,i,t)};
(all, i, sectors) (all, t, alltime)
LCLAMR(i,t) =(1-CTRTC(t)) * LCPRRR(t)
         / [CAH * CALPHA * LCRNV(i,t)^(CALPHA-1) * LCHCP(i,t)^CBETA
           + BARD - 2*LCRNV(i,t)/LRNV_R(i,t)];
(all,i,sectors)(all,t,alltime)
LRTD(i,t) = BARD*LRNV_R(i,t) - LCRNV(i,t);
VARIABLE
(CHANGE) (all, t, alltime)                                   delCTRTC(t)
 # R&D tax credit #;
(all, i, sectors) (all, t, alltime)                          crnv(i,t)
# R&D investment #;
(all, t, alltime)                                            cprrr(t)
# price of R&D good #;
(all, i, sectors) (all, t, alltime)                          clamr(i,t)
# shadow price of knowledge capital #;
(all, i, sectors) (all, t, alltime)                          ctobr(i,t)
# Tobin's-q in R&D investment #;

Update
(CHANGE)  (all, t, alltime)                        CTRTC(t) = delCTRTC(t);
(all, i, sectors) (all, t, alltime)                LCHCP(i,t) = chcp(i,t);
(all, i, sectors) (all, t, alltime)                LCRNV(i,t) = crnv(i,t);
(all, t, alltime)                                  LCPRRR(t) = cprrr(t);

!==============================================================
Foreign Tech Transfer into China through
Knowledge embodied in import  (the 1st Channel)
==============================================================!
Coefficient
(all,j,goods)                                                    BART(j)
# foreign barrier of export hi-tech good #;
(all,r,regions)(all,j,goods)(all,t,alltime)                      LERT(r,j,t)
# R&D embodiedment intensity of Traded good from region r #;
(all,r,regions)(all,j,goods_e)(all,i,sectors)(all,t,alltime)  LRTET(r,j,i,t)
# R&D Transfer via Trade Energy good into sector i, from region r #;
(all,j,goods_e)(all,i,sectors)(all,t,alltime)                 LRTET_R(j,i,t)
# R&D Transfer via Trade Energy good into sector i, sum over region r #;
(all,i,sectors)(all,t,alltime)                                 LRTET_RJ(i,t)
# R&D Transfer via Trade Energy good into sector i, sum over r and j #;
(all,r,regions)(all,j,goods_m)(all,i,sectors)(all,t,alltime)  LRTMT(r,j,i,t)
# R&D Transfer via Trade M good into sector i, from region r #;
```

```
(all,j,goods_m)(all,i,sectors)(all,t,alltime)                    LRTMT_R(j,i,t)
# R&D Transfer via Trade M good into sector i, sum over region r #;
(all,i,sectors)(all,t,alltime)                                  LRTMT_RJ(i,t)
# R&D Transfer via Trade M good j into sector i, sum over r and j #;
(all, i, sectors) (all, t, alltime)                              LRTT(i,t)
# Total R&D transfer via trade in both E and M, used in IPF #;

Read
BART  from FILE BASEDATA header "BART";

Formula
(all,r,regions)(all,j,goods)(all,t,alltime)
LERT(r,j,t) = BART(j) * LRNV(r,GOD2SEC(j),t) / V1_Y(r,j,t);
(all,r,regions)(all,j,goods_e)(all,i,sectors)(all,t,alltime)
LRTET(r,j,i,t) = LERT(r,j,t) * S_CVEFF(r,j) * S_CVEF(j) * CV1E(j,i,t);
(all,j,goods_e)(all,i,sectors)(all,t,alltime)
LRTET_R(j,i,t) = sum{r, regions, LRTET(r,j,i,t)};
(all,i,sectors)(all,t,alltime)
LRTET_RJ(i,t) = sum{j, goods_e, LRTET_R(j,i,t)};
(all,r,regions)(all,j,goods_m)(all,i,sectors)(all,t,alltime)
LRTMT(r,j,i,t) = LERT(r,j,t) * S_CVMFF(r,j) * S_CVMF(j) * CV1M(j,i,t);
(all,j,goods_m)(all,i,sectors)(all,t,alltime)
LRTMT_R(j,i,t) = sum{r, regions, LRTMT(r,j,i,t)};
(all,i,sectors)(all,t,alltime)
LRTMT_RJ(i,t) = sum{j, goods_m, LRTMT_R(j,i,t)};
(all, i, sectors) (all, t, alltime)
LRTT(i,t) = LRTET_RJ(i,t) + LRTMT_RJ(i,t);

Variable
(CHANGE)  (all,j,goods)                                           delBART(j)
# foreign barrier of export hi-tech good #;
(all,r,regions)(all,j,goods)(all,t,alltime)                       ert(r,j,t)
# R&D embodiedment intensity of Traded good from region r #;
(all,r,regions)(all,j,goods_e)(all,i,sectors)(all,t,alltime)  rtet(r,j,i,t)
# R&D Transfer via Trade E good into sector i, from region r #;
(all,r,regions)(all,j,goods_m)(all,i,sectors)(all,t,alltime)  rtmt(r,j,i,t)
# R&D Transfer via Trade M good j into sector i, from region r #;
(all,j,goods_e)(all,i,sectors)(all,t,alltime)                   rtet_r(j,i,t)
# R&D Transfer via Trade E good into sector i, sum over regions #;
(all,j,goods_m)(all,i,sectors)(all,t,alltime)                 rtmt_r(j,i,t)
# R&D Transfer via Trade M good into sector i, sum over regions #;
(all,i,sectors)(all,t,alltime)                                  rtet_rj(i,t)
# R&D Transfer via Trade E good into sector i, sum over r and j #;
(all,i,sectors)(all,t,alltime)                                  rtmt_rj(i,t)
# R&D Transfer via Trade M good into sector i, sum over r and j #;
(all, i, sectors) (all, t, alltime)                               rtt(i,t)
# total R&D transfer via trade in both E and M, used in IPF #;

Update
(CHANGE)  (all,j,goods)                     BART(j)= delBART(j);

Equation
E_ert  # knowledge intensity in trade #
(all,r,regions)(all,j,goods)(all,t,alltime)
ert(r,j,t) = 100/BART(j) *delBART(j) + rnv(r,GOD2SEC(j),t) - ouy(r,j,t);

E_rtet  # knowledge embodied E in trade #
(all,r,regions)(all,j,goods_e)(all,i,sectors)(all,t,alltime)
rtet(r,j,i,t) = ert (r,j,t) + cenff(r,j,i,t);

E_rtet_r  # knowledge embodied E in trade, sum over r #
(all,j,goods_e)(all,i,sectors)(all,t,alltime)
rtet_r(j,i,t) = sum{r, regions, LRTET(r,j,i,t)/LRTET_R(j,i,t)*rtet(r,j,i,t)};

E_rtet_rj  # knowledge embodied E in trade, sum over r and j #
(all,i,sectors)(all,t,alltime)
rtet_rj(i,t) = sum{j, goods_e,LRTET_R(j,i,t)/LRTET_RJ(i,t)*rtet_r(j,i,t)};

E_rtmt  # knowledge embodied M in trade #
(all,r,regions)(all,j,goods_m)(all,i,sectors)(all,t,alltime)
rtmt(r,j,i,t) = ert (r,j,t) + coiff(r,j,i,t);

E_rtmt_r  # knowledge embodied M in trade, sum over r  #
```

```
(all,j,goods_m)(all,i,sectors)(all,t,alltime)
rtmt_r(j,i,t) = sum{r, regions, LRTMT(r,j,i,t)/LRTMT_R(j,i,t)*rtmt(r,j,i,t)};

E_rtmt_rj  # knowledge embodied M in trade, sum over r and j #
(all,i,sectors)(all,t,alltime)
rtmt_rj(i,t) = sum{j, goods_m, LRTMT_R(j,i,t)/LRTMT_RJ(i,t)*rtmt_r(j,i,t)};

E_rtt  # total knowledge embodied in trade, both E and M #
(all, i, sectors) (all, t, alltime)
rtt(i,t) = LRTET_RJ(i,t)/LRTT(i,t) * rtet_rj(i,t)
    + LRTMT_RJ(i,t)/LRTT(i,t) * rtmt_rj(i,t);
!=================================================================
Foreign Tech Transfer into China through
Knowledge embodied in FDI (the 2nd Channel)
=================================================================!
Coefficient
                                                                  BARF
# Foreign barrier to FDI #;
(all,r,regions)(all,i,sectors)(all,t,alltime)                  LERF(r,i,t)
# R&D intensity in FDI into sector i from region r #;
(all,r,regions)(all,i,sectors)(all,t,alltime)                  LRTF(r,i,t)
# R&D Transfer via FDI into sector i from region r #;
(all,i,sectors)(all,t,alltime)                                  LRTF_R(i,t)
# R&D Transfer via FDI into sector i, sum over region r #;
Read
BARF  from FILE BASEDATA header "BARF";

Formula
(all,r,regions)(all,i,sectors)(all,t,alltime)
LERF(r,i,t) = BARF * LRNV(r,i,t) / V1_Y(r,SEC2GOD(i),t);
(all,r,regions)(all,i,sectors)(all,t,alltime)
LRTF(r,i,t) = LERF(r,i,t) * S_CVIFF(r) * S_CVIF * CVK(i,t);
(all,i,sectors)(all,t,alltime)
LRTF_R(i,t) = sum{r, regions, LRTF(r,i,t)};

Variable
(CHANGE)                                                          delBARF
# foreign barrier to FDI into China #;
(all,r,regions)(all,i,sectors)(all,t,alltime)                    erf(r,i,t)
# R&D intensity in FDI into sector i from region r #;
(all,r,regions)(all,i,sectors)(all,t,alltime)                    rtf(r,i,t)
# R&D Transfer via FDI into sector i from region r #;
(all,i,sectors)(all,t,alltime)                                    rtf_r(i,t)
# R&D Transfer via FDI into sector i, sum over region r #;

Update
(CHANGE)                                                      BARF= delBARF;

Equation
E_erf  # R&D intensity of FDI into sector i from region r #
(all,r,regions)(all,i,sectors)(all,t,alltime)
erf(r,i,t) = 100/BARF*delBARF + rnv(r,i,t) - ouy(r,SEC2GOD(i),t);

E_rtf  # R&D Transfer via FDI into sector i from region r #
(all,r,regions)(all,i,sectors)(all,t,alltime)
rtf(r,i,t) = erf(r,i,t) + cinvff(r,i,t);

E_rtf_r  # R&D Transfer via FDI into sector i, sum over region r#
(all,i,sectors)(all,t,alltime)
rtf_r(i,t) = sum {r, regions, LRTF(r,i,t)/LRTF_R(i,t) * rtf(r,i,t)};

!=====================================================
Foreign Tech Transfer into China through
Disembodied knowledge spillover (the 3rd Channel)
=====================================================!
Variable
(CHANGE)                                                       delBARD
# foreign barrier to disembodied R&D transfer to China #;
(all,i,sectors)(all,t,alltime)                                 rnv_r(i,t)
# aggregate R&D investments of technology frontier countries #;
(all,i,sectors)(all,t,alltime)                                 rtd(i,t)
# disembodied R^D spillover #;
```

```
Update
(CHANGE)                                                    BARD= delBARD;

Equation
E_rnv_r  # aggregate R&D investments of technology frontier countries #
(all,i,sectors)(all,t,alltime)
rnv_r(i,t) = sum{r, regions, LRNV(r,i,t)/LRNV_R(i,t) * rnv(r,i,t)};

E_rtd # disembodied knowledge spillover #
(all,i,sectors)(all,t,alltime)
rtd(i,t) = BARD*LRNV_R(i,t)/LRTD(i,t)*[100/BARD*delBARD + rnv_r(i,t)]
         - LCRNV(i,t)/LRTD(i,t) * crnv(i,t);

!================================================
China's knowledge Absorptive capacity for
assimilating foreign R&D inflows
================================================!
Coefficient
(all,i,sectors)(all,t,alltime)                                LRTAC(i,t)
# Absorptive capacity of R&D spillovers #;

Formula
(all,i,sectors)(all,t,alltime)
LRTAC(i,t) = LCRNV(i,t)/LRNV_R(i,t);

Variable
(all,i,sectors)(all,t,alltime)                                rtac(i,t)
# Absorptive capacity of R&D spillovers #;

Equation
E_rtac  # Absorptive capacity of R&D spillovers #
(all,i,sectors)(all,t,alltime)
rtac(i,t) = crnv(i,t) - rnv_r(i,t);

!=========================================================
Optimality condition for China's indigenous R&D investment
=========================================================!
Coefficient
(all, i, sectors) (all, t, alltime)                         CS_H5(i,t);

Formula
(all, i, sectors) (all, t, fwdtime)
CS_H5(i,t) = CALPHA*CAH*(LCRNV(i,t)^(CALPHA-1))*(LCHCP(i,t)^CBETA)
 / [CALPHA*CAH*(LCRNV(i,t)^(CALPHA-1))*(LCHCP(i,t)^CBETA)
   + BARD - 2*LCRNV(i,t)/LRNV_R(i,t)];
Equation
E_ctobr  # Tobin's-q for R&D investment TOBR #
(all, i, sectors) (all, t, alltime)
ctobr(i,t) = clamr(i,t) - cprrr(t) + 100 /(1-CTRTC(t)) * delCTRTC(t);

E_crnv   # R&D investment RNV#
(all, i, sectors) (all, t, alltime)
0 = ctobr(i,t) + CS_H5(i,t) * [(CALPHA-1)*crnv(i,t) + CBETA*chcp(i,t)]
  + (1-CS_H5(i,t)) * [2*LCRNV(i,t)/(2*LCRNV(i,t)-BARD*LRNV_R(i,t))]
  * [crnv(i,t) - rnv_r(i,t)] ;

!======================================================
Law of motion of China's knowledge capital accumulation
(Innovation Possibility Frontier)
======================================================!
Coefficient
(all, i, sectors) (all, t, alltime)                        LCHCP_II(i,t)
# indigenous innovation (II) in IPF #;
(all, i, sectors) (all, t, alltime)                        LCHCP_T(i,t)
# available knowledge pool without absorption #;
(all, i, sectors) (all, t, alltime)                        LCHCP_TT(i,t)
# foreign tech transfer (TT) in IPF #;
(all, i, sectors) (all, t, alltime)                        CS_H1(i,t);

Formula
```

```
(all, i, sectors) (all, t, alltime)
LCHCP_II(i,t) = CAH * (LCRNV(i,t)^CALPHA) * (LCHCP(i,t)^CBETA)
              - CDELTAH * LCHCP(i,t);
(all, i, sectors) (all, t, alltime)
LCHCP_T(i,t) = LRTT(i,t) + LRTF_R(i,t) + LRTD(i,t);
(all, i, sectors) (all, t, alltime)
LCHCP_TT(i,t) = LRTAC(i,t) * LCHCP_T(i,t);
(all, i, sectors) (all, t, alltime)
CS_H1(i,t) = CAH * (LCRNV(i,t)^CALPHA) * (LCHCP(i,t)^CBETA)
  / [CAH * (LCRNV(i,t)^CALPHA) * (LCHCP(i,t)^CBETA) - CDELTAH*LCHCP(i,t)];

Variable
(all, i, sectors) (all, t, alltime)                    chcp_ii(i,t);
(all, i, sectors) (all, t, alltime)                    chcp_tt(i,t);
(all, i, sectors) (all, t, alltime)                    chcp_t(i,t);

Equation
E_chcp   # Law of motion for China's knowledge capital stock #
(all, i, sectors) (all, t, fwdtime)
chcp(i, t+1) = LCHCP(i,t)/LCHCP(i,t+1) * chcp(i,t)
          + dt(t) * LCHCP_II(i,t)/LCHCP(i,t+1) * chcp_ii(i,t)
          + dt(t) * LCHCP_TT(i,t)/LCHCP(i,t+1) * chcp_tt(i,t);

E_chcp_ii       # indigenous innovation in IPF #
(all, i, sectors) (all, t, alltime)
chcp_ii(i,t) = CS_H1(i,t) * [CALPHA*crnv(i,t) + CBETA*chcp(i,t)]
          + (1-CS_H1(i,t)) *chcp(i,t);

E_chcp_tt       # foreign technology diffusion in IPF #
(all, i, sectors) (all, t, alltime)
chcp_tt(i,t) =  rtac(i,t) + chcp_t(i,t);

E_chcp_t        # global knowledge pool #
(all, i, sectors) (all, t, alltime)
chcp_t(i,t) =  LRTT(i,t)/LCHCP_T(i,t) * rtt(i,t)
         +  LRTF_R(i,t)/LCHCP_T(i,t) * rtf_r(i,t)
         +  LRTD(i,t)/LCHCP_T(i,t) * rtd(i,t);

!============================================================
Law of motion for the shadow price of China's knowledge capital
============================================================!
Coefficient
(all, i, sectors) (all, t, fwdtime)                     CS_H2(i,t);
(all, i, sectors) (all, t, fwdtime)                     CS_H3(i,t);
(all, i, sectors) (all, t, endtime)                     CS_H4(i,t);

Formula
(all, i, sectors) (all, t, fwdtime)
CS_H2(i,t) = [1 + dt(t)*(CINTR + CDELTAH) - dt(t)*CAH*CBETA
           * (LCRNV(i,t)^CALPHA)*(LCHCP(i,t)^(CBETA-1))]
           * LCLAMR(i,t) / LCLAMR(i,t+1);

(all, i, sectors) (all, t, fwdtime)
CS_H3(i,t) = [- dt(t)*CAH*CBETA*(LCRNV(i,t)^CALPHA)*(LCHCP(i,t)^(CBETA-1))]
          / [1 + dt(t)*(CINTR + CDELTAH) - dt(t)*CAH*CBETA
            *(LCRNV(i,t)^CALPHA)*(LCHCP(i,t)^(CBETA-1))];

(all, i, sectors) (all, t, endtime)
CS_H4(i,t) = [- CAH*CBETA*(LCRNV(i,t)^CALPHA)*(LCHCP(i,t)^(CBETA-1))]
          / [CINTR + CDELTAH - CAH*CBETA*(LCRNV(i,t)^CALPHA)
          *(LCHCP(i,t)^(CBETA-1))];

Equation
E_clamr  # Law of motion for shadow price of knowledge capital #
(all, i, sectors) (all, t, fwdtime)
clamr(i,t+1) =
           CS_H2(i,t) * [clamr(i,t) + CS_H3(i,t)*(CALPHA*crnv(i,t)+(CBETA-1)*chcp(i,t))]
           + (1-CS_H2(i,t))*[cphc(i,t) - 100/(1-CTCOR(t))* delCTCOR(t)];

E_clamrend # boundary condtion for shadow price of knowledge capital #
(all, i, sectors) (all, t, endtime)
CS_H4(i,t) * [CALPHA*crnv(i,t)+(CBETA-1)*chcp(i,t)] + clamr(i,t)
           = cphc(i,t) - 100/(1-CTCOR(t))* delCTCOR(t) ;
```

4.D Economic Globalization Policy Shocks

1) Removal of import tariffs

	China's import tariff rate	Economy globalization
1 ELEC	5%	0%
2 GAS	5%	0%
3 PETROLEUM	5%	0%
4 COAL	8%	0%
5 OIL_GAS	5%	0%
6 MINING	8%	0%
7 AGRIC	20%	0%
8 FORES	5%	0%
9 DURABLE	12%	0%
10 NONDURABLE	15%	0%
11 TRANSPORT	5%	0%
12 SERVICE	5%	0%

2) Removal of FDI barriers

China's domestic corporate income tax is 25%, and the preferable tax rate offered to the operation of MNCs is a half of that domestic tax rate. The FDI tax rate is thus equivalent to 25% * 50% = 12.5%. The policy shock of economy globalization cut this FDI tax rate from 12.5% to 0%.

Source: WTO (2010), UNCTAD (2010a,b).

Chapter 5

International Knowledge Spillover and Technology Externality: Why Multilateral R&D Coordination Matters for Global Climate Governance*

Abstract: Sustainability of [illegible] an ambition-based international climate agreement with a technology-oriented role has been placed high upon the policy and research agenda. This paper examines the mechanisms of multilateral technology coordination and its effect on global climate mitigation. We firstly present an analytical framework that describes how multilateral R&D coordination works on a climate mitigation issue. This mechanism is then quantitatively examined in a multi-region global numerical model that explicitly considers the technology externality resulting from cross-country knowledge spillovers. Results show that: (1) by internalizing the externality of the global knowledge spillovers, multilateral R&D coordination induces more climate-specific R&D investment [illegible] diffusion; (2) innovative efforts [illegible] knowledge creation and application, which [illegible] in participating nations; (3) [illegible] climate agreement [illegible] climate mitigation [illegible] their collective efforts in global climate governance.

Keywords: Knowledge spillover; Technology Coordination; [illegible]

* This chapter is based on the paper submitted to Resource and Energy Economics [illegible]: "International knowledge spillover and technology externality: Why multilateral R&D coordination matters for global climate governance".

Chapter 5

International Knowledge Spillover and Technology Externality: Why Multilateral R&D Coordination Matters for Global Climate Governance*

Abstract: Suggestions of complementing an emission-based international climate agreement with a technology-oriented one has been placed high upon the policy and research agenda. This paper examines the mechanism of international technology coordination and its effect on global climate mitigations. We firstly present an analytical framework that describes how multilateral R&D coordination works in a climate mitigation context. This mechanism is then quantitatively examined in a multi-region global numerical model that explicitly considers the technology externality resulting from cross-country knowledge diffusions. Results show that: (1) By internalizing the externality of reciprocal knowledge diffusions, multilateral R&D coordination induces more country-specific R&D investment and cross-country knowledge diffusions; (2) Innovative efforts enhanced by international R&D coordination facilitate new knowledge creation and application, which stimulates economic growths and carbon savings in participating nations; (3) Multilateral R&D coordination can synergize with traditional emission-based climate agreements to help lower climate compliance costs, hence raising climate mitigation incentives of major carbon emitters and the environmental effectiveness of their collective efforts in global climate governance.

Keywords: Knowledge Spillover; Technology Coordination; Climate Policy Model

* This chapter is based on the paper submitted to *Resources and Energy Economics* as Jin, W., "International knowledge spillover and technology externality: Why multilateral R&D coordination matters for global climate governance."

5.1 Introduction

In pursuit of a low-carbon and knowledge-based economy, both developed and developing countries have stepped up efforts to boost "green" competitiveness through technological innovation. This kind of strategy finds its clearest expression in the massive growth in R&D investment. While the U.S., the E.U., and Japan remain leaders in science and technology (S&T) innovation, increased competitions from the emerging economies, notably the BRICS countries, suggest a changing geography of global innovation (NSB, 2012; OECD, 2012).[1] This new landscape has remarkably transcended the former innovation pattern of the Triad regions (U.S., E.U., and Japan), with the emerging economies becoming increasingly engaged in the international S&T scene as new hubs of global innovation.

In an interconnected globalized world, the emergence of multiple hubs of innovation is anticipated to create cross-country knowledge diffusions and technology interactions. On the one hand, as the traditional aspect of globalization, individual national economies have been increasingly integrated into the globalized network of production and distribution through multilateral trade and investment (globalization of production), which enables an extensive dissemination of technologies via cross-border transaction of material, capital, and products (UNCTAD, 2010a, b; WTO, 2010). On the other hand, as the modern aspect of globalization, internationalization of R&D enhances a tendency for reliance of indigenous innovation on external knowledge sources (globalization of innovation), individual countries have taken measures to harness international heightened mobility of knowledge for building indigenous innovative capacity (OECD, 1997; UNCTAD, 2005).

The emergence of multiple innovation hubs and their technology interactions provides significant implications for climate mitigation strategies. First, as existing emission-based international climate agreements (e.g., the Kyoto Protocol) become increasingly flawed due to a lack of mechanism to encourage mitigation incentives, a technology-oriented agreement that aims for multilateral innovation cooperation should be regarded as a key building block

[1] This chaning landscape of global innovation is reflected in three aspects: 1) Absolute size: R&D spending in Asia surpassed the E.U. levels and is likely to overtake U.S. in the next five years, which is due to striking R&D growth in China (the world's third largest R&D investor); 2) Growth rate: the current growth pace of R&D in the Asian market, notably China, is considerably higher than that in G7 markets; 3) R&D intensity: a flat level remain in the G7 markets, but the growth market has nearly doubled its R&D intensity over the last decade.

of the post-2012 climate policy architecture. Since the global innovation hubs are also major carbon-emitting regions in the world, technology cooperation among the global innovation hubs thus provides one option to improve their incentives of participating in global climate mitigation (Aldy et al., 2003; Barrett, 2003; Barrett and Stavins, 2003; Newell, 2008)

Second, the traditional climate technology strategies still put an overly narrow focus on the North-South direct technology transfer for climate mitigation and adaptation, which thus ignores the potential South-North technology feedback as well as South-South technology cooperation (Brewer, 2008; 2009). However, as the emerging economies increasingly become active players in the international R&D race, managing the global issue like climate stabilization also requires establishing an enabling framework that facilitates cross-country technology cooperation, where the North technology incumbents have a channel to learn the experience, expertise and knowledge created by the South new entrants.[2]

Third, the current climate technology strategies implemented by individual countries are unilateral, fragmented, and uncoordinated, taking no account of the positive technology externality resulting from cross-country knowledge diffusion.[3] To internalize the externality, a framework of multilateral cooperation on climate-related technology should be built by particular international organizations to coordinate innovation in individual countries.[4] By doing that, global collective innovative efforts can be enhanced to provide and share more knowledge that favors low-carbon innovation and carbon savings at a global scale.

Therefore, I am motivated to study how international R&D coordination works and its effect on reducing climate mitigation cost. In explicit, I aim to consider the following issues: 1) How does cross-country knowledge diffusion create the positive technology externality; 2) Why does technology externality provide an opportunity of multilateral R&D coordination for climate mitigation; 3) What is the effect of international R&D coordination on economic

[2] For example, to support international energy technology cooperation, the IEA should consider measures to more regularly and deeply involve non-OCED countries (e.g., the BRICS countries) in IEA programs. By accelerating the accession of such countries to the IEA, international climate technology cooperation can be achieved on a large scale (de Coninck et al., 2008; Newell, 2008).

[3] Due to the existence of double externality (environment and technology externality), climate technology strategies should thus be formulated to internalize the positive technology externality, beyond emission-based climate policy instruments that correct for the environmental externality of carbon emissions (Nordhaus, 2011; Popp, 2011).

[4] Some international agreements on climate-friendly technology cooperation are developed in recently years, including the Asia-Pacific Partnership on Clean Development and Climate (APP), International Energy Agency Implementing Agreements (IEA-IA).

and environmental performance of participating countries; 4) To what extent can technology cooperation synergize with emission-based instruments to mitigate climate compliance cost.

To address these issues, I firstly present a simple analytical framework that describes the mechanism of international R&D coordination for climate mitigation. Next, this mechanism is incorporated into a multi-region global numerical model, so that the effect of cross-country R&D coordination can be quantitatively examined. Based on both analytical and numerical studies, I aim to demonstrate the importance of international R&D coordination for global climate governance.

As a needed complement to the existing literature, this study contributes to climate policy analysis in the following three aspects: 1) The "stock of knowledge" approach is used to explicitly represent cross-country technology diffusion and the mechanism of international climate-related technology cooperation;[5] 2) A comprehensive framework is provided to fully capture the various technology diffusion channels of through trade, FDI, and disembodied knowledge spillover;[6] 3) A new innovation pattern of cross-country technology interaction is explicitly considered, particularly the South-North technology feedback and South-South technology cooperation.[7]

The organization of this chapter is as follows: Section 5.2 presents a simple framework of analyzing international R&D coordination for climate mitigation. Section 5.3 describes the basic structure of a multi-region global numerical model, with an emphasis on modeling

[5] In the field of international climate-related technology cooperation, for theoretical expositions, see Xepapadeas (1995), Barrett (2006), Kolstad (2007), Golombek and Hoel (2005, 2008, 2011), Heal and Tarui (2010), Hoel and de Zeeuw (2010), Mario and Werf (2008), Helm and Wirl (2011), Helm and Pichler (2011), Greaker and Hagem (2010); For numerical analysis, see Buchner and Carraro (2005); Carraro and Siniscalco (1997); Kemfert (2004); Nagashima and Dellink (2008); Lessmann and Edenhofer (2011); De Cian and Tavono (2012). To complement the existing literature, this study uses the "stock of knowledge" approach to investigate the mechanism of international R&D coordination and its impact on global climate mitigation.

[6] Only one type of TD channel is modeled in existing climate modeling works like Hübler (2011), Leimbach and Baumstark (2010), Leimbach and Edenhofer (2007), Leimbach and Eisenack (2009), Bosetti et al. (2008, 2011), De Cian and Tavoni (2012), Buonanno et al. (2003). However, some empirical studies show that firms do not merely conduct a single type of economic activity associated with technology diffusion, but perform several such activities simultaneously (e.g., Clerides et al., 1998; Keller, 2004).

[7] Most of existing climate policy modeling works only capture the North-South unidirectional knowledge diffusions (e.g., Hübler, 2011; Bosetti et al., 2008, 2011). However, as the emerging economies increasingly become key players in global innovation, modeling attempts should realistically reflect the new innovation pattern of multidirectional technology interaction.

cross-country knowledge diffusions and multilateral R&D coordination. Simulation results and discussions are provided in Section 5.4. Section 5.5 concludes.

5.2 Analytical Framework

In this section, a simple analytical framework will be presented to describe the mechanism of international R&D coordination and its effect on technical change (TC) and carbon emissions reductions. In the spirit of the "stock of knowledge" approach that treats knowledge as a production factor,[8] I model the production technology used in the energy sector as a two-tier nested CES function. In producing knowledge-embodied energy service (Y), knowledge (H) substitutes for a composite of energy input at the top tier. The energy input composite is in turn made up of "dirty" fossil energy (E_D) and "clean" non-fossil energy (E_C) at the bottom tier. CES parameter σ_Y controls the substitution possibility between energy and knowledge input at the top tier, and σ_E controls the substitution possibility between the two energy input varieties. Given this production technology, the energy firm solves a cost minimization problem as:

$$\begin{aligned} &\min_{E_C,E_D} \; P_D \cdot E_D + P_C \cdot E_C \\ &\text{s.t.} \quad \left[\left(E_D^{\sigma_E} + E_C^{\sigma_E}\right)^{\frac{\sigma_Y}{\sigma_E}} + H^{\sigma_Y}\right]^{\frac{1}{\sigma_Y}} = Y; \qquad E_C > 0; \qquad \bar{\kappa} \geq E_D > 0 \end{aligned} \tag{5.1}$$

where P_D, P_C are the prices of "dirty" and "clean" energy input, respectively. For simplicity, I assume that one unit of fossil energy input (E_D) generates one unit of carbon emission (κ), so that $\kappa = E_D$. In the presence of carbon constraints, the firm is capped by an emission limit $\bar{\kappa}$, so the levels of carbon emissions from fossil energy use should be below this emissions limit, $E_D \leq \bar{\kappa}$. Given the production technology and emission constraints, the firm solves the cost minimization problem as outlined in Eq. (5.1), where the corresponding Lagrangian can be formulated as:

$$L = -(P_D \cdot E_D + P_C \cdot E_C) + \lambda_Y \cdot \left[\left(E_D^{\sigma_E} + E_C^{\sigma_E}\right)^{\frac{\sigma_Y}{\sigma_E}} + H^{\sigma_Y} - Y^{\sigma_Y}\right] + \lambda_D \cdot (\bar{\kappa} - E_D) + \lambda_C \cdot E_C \tag{5.2}$$

---

[8] The literature models the effect of knowledge application on TC through three routes: a direct impact on the carbon emission intensity (Nordhaus, 2002; Buonanno et al., 2003); a reduction in the mitigation cost function (Goulder and Mathai, 2000); knowledge substitution for physical inputs (Goulder and Schneider, 1999; Sue Wing, 2003; Popp, 2004).

where $\lambda_Y, \lambda_D, \lambda_C$ denote the Lagrangian multipliers corresponding to the three constraints in Eq. (5.1). In the presence of emission caps, the permit constraint reaches the boundary condition ($E_D = \overline{\kappa}$) where carbon abatement occurs. I hence derive an expression revealing the relationship between marginal abatement cost (MAC) and knowledge input as:[9]

$$\lambda_D = -P_D + P_C \cdot \left[\left(Y^{\sigma_Y} - H^{\sigma_Y} \right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E} \right]^{\frac{1-\sigma_E}{\sigma_E}} \cdot \overline{\kappa}^{\sigma_E - 1} \tag{5.3}$$

where λ_D is the Lagrangian multiplier associated with carbon permit constraint. It denotes the shadow price of carbon emission permit, with its economic meaning being the additional production cost savings from relaxing an extra unit (marginally) of carbon permit. By the same token, it also represents the additional production costs incurred from tightening an extra unit of emission constraint – the marginal carbon abatement cost.

For the sake of convenience, I rewrite the Eq. (5.3) to work with a logarithmic (percentage change) form as:

$$\widehat{\lambda_D} = -\frac{P_D}{\lambda_D} \cdot \widehat{P_D} + \frac{P_C \cdot \left[\left(Y^{\sigma_Y} - H^{\sigma_Y} \right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E} \right]^{\frac{1-\sigma_E}{\sigma_E}} \cdot \overline{\kappa}^{\sigma_E - 1}}{\lambda_D} \cdot \left[\widehat{P_C} + (\sigma_E - 1) \cdot \widehat{\overline{\kappa}} + \left(\frac{1-\sigma_E}{\sigma_E} \right) \cdot \widehat{\left[\left(Y^{\sigma_Y} - H^{\sigma_Y} \right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E} \right]} \right] \tag{5.4}$$

where a hat symbol (^) represents the percentage change in corresponding variables. To simplify the notations of variables, I assume that energy price (P_D, P_C) and carbon permit constraint ($\overline{\kappa}$) are set exogenously in the partial equilibrium environment, with their percentage-change values being equal to zero. Then, the Eq. (5.4) can be simplified as:[10]

$$\begin{aligned}
\widehat{\lambda_D} &= A \cdot \frac{1-\sigma_E}{\sigma_E} \cdot \widehat{\left[\left(Y^{\sigma_Y} - H^{\sigma_Y} \right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E} \right]} \\
&= A \cdot \frac{1-\sigma_E}{\sigma_Y} \cdot \frac{\left(Y^{\sigma_Y} - H^{\sigma_Y} \right)^{\frac{\sigma_E}{\sigma_Y}}}{\left(Y^{\sigma_Y} - H^{\sigma_Y} \right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E}} \cdot \left(\frac{Y^{\sigma_Y}}{Y^{\sigma_Y} - H^{\sigma_Y}} \cdot \sigma_Y \cdot \widehat{Y} - \frac{H^{\sigma_Y}}{Y^{\sigma_Y} - H^{\sigma_Y}} \cdot \sigma_Y \cdot \widehat{H} \right) \\
&= -A \cdot (1-\sigma_E) \cdot \frac{\left(Y^{\sigma_Y} - H^{\sigma_Y} \right)^{\frac{\sigma_E}{\sigma_Y}}}{\left(Y^{\sigma_Y} - H^{\sigma_Y} \right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E}} \cdot \frac{H^{\sigma_Y}}{Y^{\sigma_Y} - H^{\sigma_Y}} \cdot \widehat{H}
\end{aligned} \tag{5.5}$$

---

9 For the derivation of Eq. (5.3), see Appendix 5.A.

10 Here we define a term $A = (1/\lambda_D) \cdot P_C \cdot \left[\left(Y^{\sigma_Y} - H^{\sigma_Y} \right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E} \right]^{\frac{1-\sigma_E}{\sigma_E}} \cdot \overline{\kappa}^{\sigma_E - 1}$

where, for an exogenously given level of output Y ($\widehat{Y}=0$), it is found that the MAC declines ($\widehat{\lambda_D}<0$) when the input of knowledge augments ($\widehat{H}>0$) as an outcome of R&D investment.

Next, I introduce a two-country (South-North) knowledge diffusion model. Assume that, for the South, both its indigenous R&D (R_S) and absorptions of foreign knowledge diffusion (R_S^*) contribute to the accumulation of knowledge available in that country, which can be expressed as:

$$H_S = R_S + R_S^* = R_S + \gamma_S \cdot R_S^{KD} = R_S + \frac{R_S}{R_S + R_N} \cdot (R_S + R_N - R_S) \tag{5.6}$$

where R_S^{KD} is foreign knowledge diffusion into the South, expressed as the unexplored gap between global R&D ($R_S + R_N$) and the South's indigenous R&D (R_S). γ_S reflects the South's knowledge absorptive capacity, expressed as a ratio of the South's indigenous R&D relative to global total R&D. The product of R_S^{KD} and γ_S reflects the South's absorptions of foreign diffused knowledge R_S^*. Foreign knowledge diffusion (R_S^{KD}), corrected by local knowledge absorptive capacity, is a perfect substitute for indigenous R&D (R_S) in building the South's knowledge. In symmetry, knowledge creation in the North (H_N) depends on both indigenous R&D (R_N) and absorptions of foreign knowledge diffusion (R_N^*) as:

$$H_N = R_N + R_N^* = R_N + \frac{R_N}{R_N + R_S} \cdot (R_N + R_S - R_N) \tag{5.7}$$

Again, it is convenient to rewrite Eqs. (5.6)-(5.7) in a logarithmic form to represent the percentage change of variables (denoted by "^") as:

$$\widehat{H_S} = \frac{R_S \cdot (R_S^2 + 2 \cdot R_S \cdot R_N + 2 \cdot R_N^2)}{H_S \cdot (R_S + R_N)^2} \cdot \widehat{R_S} + \frac{R_S^2 \cdot R_N}{H_S \cdot (R_S + R_N)^2} \cdot \widehat{R_N} \tag{5.8}$$

$$\widehat{H_N} = \frac{R_N \cdot (R_N^2 + 2 \cdot R_N \cdot R_S + 2 \cdot R_S^2)}{H_N \cdot (R_N + R_S)^2} \cdot \widehat{R_N} + \frac{R_N^2 \cdot R_S}{H_N \cdot (R_N + R_S)^2} \cdot \widehat{R_S} \tag{5.9}$$

Combine Eqs. (5.8)-(5.9) with Eq. (5.5), I derive an expression that reveals the relationship between the MAC reduction and R&D investment in both countries as:

The South:

$$
\begin{cases}
\hat{\lambda}_S = -A_S \cdot (1-\sigma_E) \cdot \dfrac{\left(Y_S^{\sigma_Y} - H_S^{\sigma_Y}\right)^{\frac{\sigma_E}{\sigma_Y}}}{\left(Y_S^{\sigma_Y} - H_S^{\sigma_Y}\right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}_S^{\sigma_E}} \cdot \dfrac{H_S^{\sigma_Y}}{Y_S^{\sigma_Y} - H_S^{\sigma_Y}} \cdot \widehat{H}_S \\
\widehat{H}_S = \dfrac{R_S \cdot (R_S^2 + 2 \cdot R_S \cdot R_N + 2 \cdot R_N^2)}{H_S \cdot (R_S + R_N)^2} \cdot \widehat{R}_S + \dfrac{R_S^2 \cdot R_N}{H_S \cdot (R_S + R_N)^2} \cdot \widehat{R}_N
\end{cases}
\tag{5.10}
$$

The North:

$$
\begin{cases}
\hat{\lambda}_N = -A_N \cdot (1-\sigma_E) \cdot \dfrac{\left(Y_N^{\sigma_Y} - H_N^{\sigma_Y}\right)^{\frac{\sigma_E}{\sigma_Y}}}{\left(Y_N^{\sigma_Y} - H_N^{\sigma_Y}\right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}_N^{\sigma_E}} \cdot \dfrac{H_N^{\sigma_Y}}{Y_N^{\sigma_Y} - H_N^{\sigma_Y}} \cdot \widehat{H}_N \\
\widehat{H}_N = \dfrac{R_N \cdot (R_N^2 + 2 \cdot R_N \cdot R_S + 2 \cdot R_S^2)}{H_N \cdot (R_N + R_S)^2} \cdot \widehat{R}_N + \dfrac{R_N^2 \cdot R_S}{H_N \cdot (R_N + R_S)^2} \cdot \widehat{R}_N
\end{cases}
\tag{5.11}
$$

where, for any individual counties, both indigenous and foreign R&D investment contribute to domestic knowledge creation. As the newly created knowledge is applied in production to substitute for fossil energy input, the MAC will fall with $\hat{\lambda} < 0$.

To simplify the notations, I assume that both nations have the same levels of indigenous R&D ($R_S = R_N$) and hence knowledge input ($H_S = H_N$) in a symmetric two-country model. Eqs. (5.10)-(5.11) can thus be simplified as a reduce-form expression showing the relationship between the MAC reduction and R&D investment in both countries as:

$$\hat{\lambda}_S = -\widehat{R}_S - \varepsilon \cdot \widehat{R}_N \tag{5.12}$$

$$\hat{\lambda}_N = -\widehat{R}_N - \varepsilon \cdot \widehat{R}_S \tag{5.13}$$

where ε is the foreign innovation elasticity of domestic MAC reduction, reflecting the effect of foreign R&D on domestic MAC reduction. Its value can be estimated by normalizing the coefficients associated with variables the $\widehat{R}_N, \widehat{R}_S$: $\varepsilon = R_S^2 \cdot R_N / (R_S^3 + 2 \cdot R_S^2 \cdot R_N + 2 \cdot R_S \cdot R_N^2) = 0.2$, given $R_S = R_N$ in a symmetric two-country model. This implies that foreign R&D, through cross-country knowledge diffusion, has a positive externality effect to reduce domestic MAC. But this effect is secondary to indigenous R&D, since the indigenous innovation elasticity of domestic MAC reduction equals 1.

Assume that, the South firm attempts to undertake indigenous R&D for MAC reduction (getting the absolute level of MAC reduction $-\hat{\lambda}$ as close as possible to some desirable level of MAC reduction target, $\bar{\lambda}>0$) without, however, spending more R&D expenditure (for the purpose of profit maximization). The South firm hence faces a problem of minimizing some cost function L_S, subject to the Eq. (5.12) as:

$$\min \ L_S = \frac{1}{2}\cdot(-\hat{\lambda}_S - \bar{\lambda})^2 + \frac{\theta}{2}\cdot\hat{R}_S^{\,2} \tag{5.14}$$

$$\text{s.t.} \quad \hat{\lambda}_S = -\hat{R}_S - \varepsilon\cdot\hat{R}_N$$

in a similar fashion, the North firm faces a problem of minimizing some cost function L_N, subject to the Eq. (5.13) as:

$$\min \ L_N = \frac{1}{2}\cdot(-\hat{\lambda}_N - \bar{\lambda})^2 + \frac{\theta}{2}\cdot\hat{R}_N^{\,2} \tag{5.15}$$

$$\text{s.t.} \quad \hat{\lambda}_N = -\hat{R}_N - \varepsilon\cdot\hat{R}_S$$

Suppose that, both countries choose the levels of R&D spending independently, taking no account of the possible repercussions of cross-country knowledge diffusions. In this case, each country chooses R&D spending levels conditional upon the other's R&D plan - the so-called *uncoordinated innovation*. In explicit, the South firm solves the problem in Eq. (5.14) and yield its best response function, RF_S, as follows:

$$\frac{\partial L_S}{\partial \hat{R}_S} = (\hat{R}_S + \varepsilon\cdot\hat{R}_N - \bar{\lambda}) + \theta\cdot\hat{R}_S = 0 \qquad \Rightarrow \qquad \hat{R}_S = \frac{\bar{\lambda} - \varepsilon\cdot\hat{R}_N}{1+\theta} \tag{5.16}$$

where the best response function RF_S relates the South's optimal (non-coordinated) level of R&D spending to the MAC reduction target and the R&D spending levels of the North. Similarly, the North firm has its best response function, RF_N, as follows:

$$\frac{\partial L_N}{\partial \hat{R}_N} = (\hat{R}_N + \varepsilon\cdot\hat{R}_S - \bar{\lambda}) + \theta\cdot\hat{R}_N = 0 \qquad \Rightarrow \qquad \hat{R}_N = \frac{\bar{\lambda} - \varepsilon\cdot\hat{R}_S}{1+\theta} \tag{5.17}$$

In a non-coordinated innovation equilibrium, one country sets its R&D spending levels according to the other country's R&D plan (as characterized by the best response functions). The non-coordinated levels of R&D spending can hence be obtained by finding the intersection of RF_S and RF_N as:

$$\widehat{R}_S^{NC} = \widehat{R}_N^{NC} = \frac{\overline{\lambda}}{1+\varepsilon+\theta} \tag{5.18}$$

where the superscript "NC" refers to the non-coordinated innovation. As Fig. 5.1 shows, the two best response functions are drawn as RF_S and RF_N, respectively. The non- coordinated innovation is at point "NC", where the two best response functions intersect.

By comparison, both countries in a coordinated innovation take into account the positive externality resulting from cross-country knowledge diffusion - the so-called *coordinated innovation.* One way to analyze the innovation coordination is to assume that both countries relinquish controls over R&D to an international coordinating body that enforces multilateral technology cooperation.[11] This coordinating body is instructed to minimize total loss function, $L_S + L_N$, by choosing R&D spending levels in both individual countries as:

$$\begin{aligned} &\min\ L_S + L_N = \frac{1}{2}\cdot(-\widehat{\lambda}_S - \overline{\lambda})^2 + \frac{\theta}{2}\cdot\widehat{R}_S^{\,2} + \frac{1}{2}\cdot(-\widehat{\lambda}_N - \overline{\lambda})^2 + \frac{\theta}{2}\cdot\widehat{R}_N^{\,2} \\ &\text{s.t.}\quad \widehat{\lambda}_S = -\widehat{R}_S - \varepsilon\cdot\widehat{R}_N, \quad \widehat{\lambda}_N = -\widehat{R}_N - \varepsilon\cdot\widehat{R}_S \end{aligned} \tag{5.19}$$

Solving the problem yields the F.O.C.:

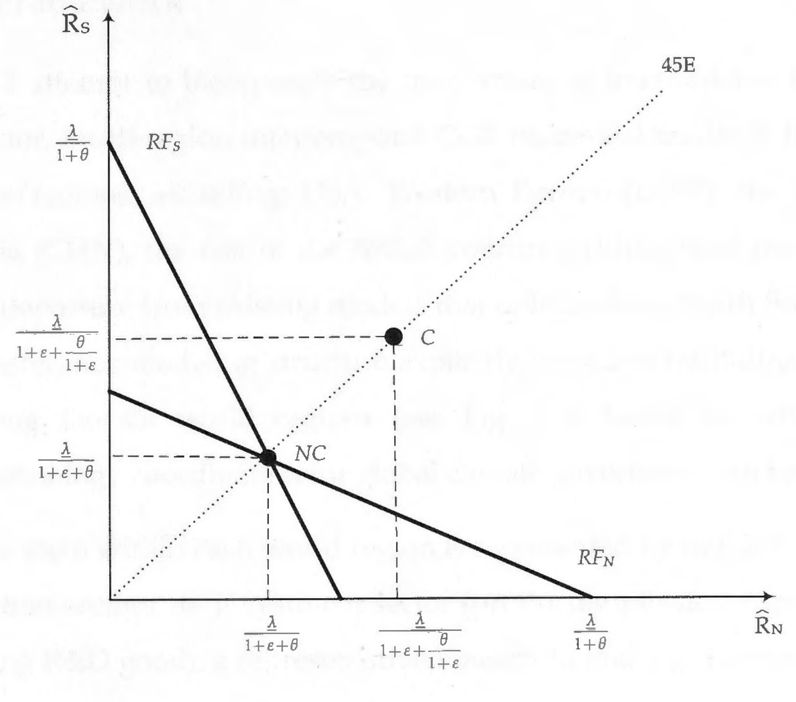
$$\begin{cases} \dfrac{\partial(L_S + L_N)}{\partial\widehat{R}_S} = (\widehat{R}_S + \varepsilon\cdot\widehat{R}_N - \overline{\lambda}) + \underbrace{\varepsilon\cdot(\widehat{R}_N + \varepsilon\cdot\widehat{R}_S - \overline{\lambda})}_{\text{South-to-North R\&D Spillover}} + \theta\cdot\widehat{R}_S = 0 \\ \dfrac{\partial(L_S + L_N)}{\partial\widehat{R}_N} = (\widehat{R}_N + \varepsilon\cdot\widehat{R}_S - \overline{\lambda}) + \underbrace{\varepsilon\cdot(\widehat{R}_S + \varepsilon\cdot\widehat{R}_N - \overline{\lambda})}_{\text{North-to-South R\&D Spillover}} + \theta\cdot\widehat{R}_N = 0 \end{cases} \tag{5.20}$$

Compare the F.O.C. in the coordinated innovation (see Eq. (5.20)) with the ones in the non-coordinated innovation (see Eqs. (5.16)-(5.17)), we find in innovation coordination R&D spending plan set in one country would take into account its positive externality effect on facilitating innovation in the other country, as characterized by the terms premultiplied by ε. Solving the Eq. (5.20) for $\widehat{R}_S$ and $\widehat{R}_N$ yields the coordinated levels of R&D spending as:

$$\widehat{R}_S^{C} = \widehat{R}_N^{C} = \frac{\overline{\lambda}}{1+\varepsilon+\dfrac{\theta}{1+\varepsilon}} \tag{5.21}$$

[11] The OECD is generally perceived as such an international coordinating body that influences innovation policy making in its member countries. Meanwhile, given the centrality of the IEA in global energy and climate governance, the IEA may be an appropriate body for managing international energy technology cooperation.

Figure 5.1: Mechanism ofinternational R&D coordination
in a symmetric two-country model



Note: The points "NC" and "C" denote non-coordinated and coordinated innovation equilibrium, respectively. By internalizing the positive externality of cross-country technology diffusion, individual countries in the coordinated innovation equilibrium are committed to undertake higher levels of R&D spending.

where the superscript "C" refers to the coordinated innovation. The relative size of R&D spending in coordinated and non- coordinated cases can be judged by comparing Eq. (5.18) with Eq. (5.21). With $\varepsilon > 0$, say 0.2, the coordinated innovation involves a higher level of R&D spending in both countries. This is illustrated in Fig. 5.1, where point "C" designates the coordinated innovation equilibrium.

The analytical results provide a following intuition: In the absence of R&D coordination, individual countries undertake independent innovative activities but ignore the technology externality of cross-country knowledge diffusions. Accordingly, they underestimate the beneficial effect of indigenous R&D on reducing foreign MAC, and hence set R&D spending levels that are relatively low. In contrast, in the presence of R&D coordination, individual countries are instructed by a coordinating body to undertake higher levels of R&D spending for internalizing the positive technology externality. As a result, global collective innovative efforts would be enhanced, with more provisions of public knowledge that favors innovation and MAC reductions in participating countries.

5.3 Numerical Model

5.3.1 Basic Framework

In this section, I attempt to incorporate the mechanism of international R&D coordination into a multi-sector, multi-region intertemporal CGE numerical model.[12] It distinguishes six world countries/regions, including: USA, Western Europe (EUW), the rest of the OECD (ROECD), China (CHN), the rest of the BRICS countries (BRIS), and the rest of the world (ROW).[13] As a departure from existing models that only capture North-South unidirectional technology transfer, our modeling structure explicitly considers multidirectional technology diffusions among the six world regions (see Fig. 5.2), based on which the issues of international technology coordination for global climate governance can be investigated.

Economic system within each world region is represented by multiple agents, including: Twelve production sectors, an investment sector (producing physical capital goods), a R&D sector (producing R&D good), a representative household and a government. To be relevant to climate policy studies, the twelve production sectors consist of five energy sectors and seven non-energy sectors.[14] Carbon emissions are calculated based on carbon intensities of fossil fuel inputs (coal, oil and natural gas) used in intermediate production and final use.

Economic behaviors of multiple agents within each region are modeled in line with the general equilibrium structure, which outlines input-output (IO) circular flows of multiple commodities and primary factors within the economy (see Fig. 3.1 in Chapter 3). There are 12 produced commodities and corresponding production sectors, indexed by the row subscript $j\,(j=1,2,...,12)$ and the column subscript $i\,(i=1,2,...,12)$, respectively; 3 types of primary factors (labor, physical capital, knowledge capital), indexed by the subscript $f\,(f=L,K,H)$; 5 types of final use (consumption, investment, R&D, government, export), indexed by the subscript $d\,(d=C,I,R,G,X)$. Intersectoral transactions in intermediate productions are represented by the $j \times i$ matrix; Inputs of primary factors in production are indicated by the $f \times i$ matrix; Final uses of produced commodities are represented by the $j \times d$ matrix.

---

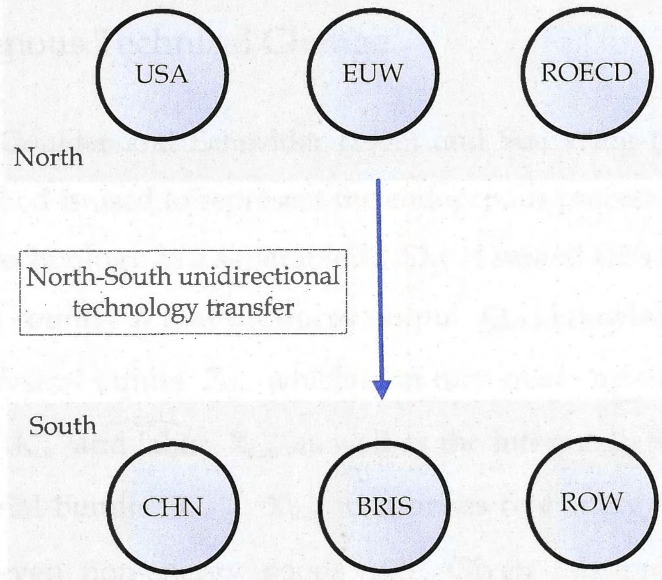
12 The intertemporal optimization CGE models is in the spirit of the seminal works by Jorgenson and Wilcoxen (1990), Malakellis (1994), Bovenberg and Goulder (1996), McKibbin and Wilcoxen (1998), Dixon et al. (2005).

13 For the country composition of regions, see Appendix 5.B.

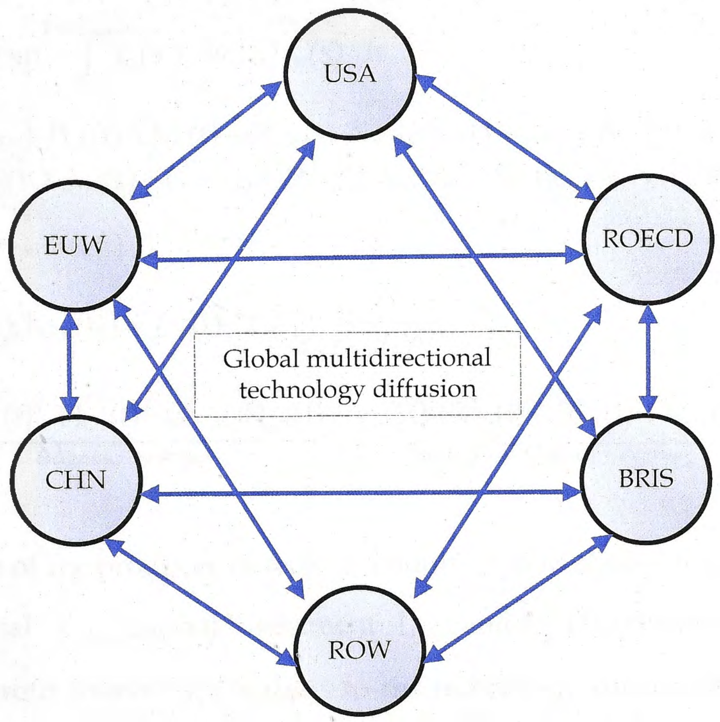
14 For the model sectoral classification and mapping by reference to the GTAP, see Appendix 5.B.

Figure 5.2: International technology regimes for global climate governance

(a)



(b)



Note: (a) North-South unidirectional technology transfers;
(b) Global multidirectional technology diffusion

From this IO framework to a numerical CGE model, I describe the decision problems facing these economic agents and characterize their behaviors in a decentralized equilibrium. To endogenously represent TC, our model broadens the traditional CGE structure by adding R&D investment and knowledge input. This will be articulated in the following sections.

5.3.2 Endogenous Technical Change

In the spirit of Goulder and Schneider (1999) and Sue Wing (2001; 2003), the "stock of knowledge" method is used to represent the endogenous process of TC. In explicit, I model the production technology as a separable KLEM-H nested CES function. For the firm in a given sector i in country n that produces output $Q_{i,n}$, knowledge $H_{i,n}$ substitutes for a composite of physical inputs $Z_{i,n}$, which is in turn made up of primary factor inputs of physical capital $K_{i,n}$ and labor $X_{iL,n}$, as well as the intermediate inputs of energy bundle $X_{iE,n}$ and material bundle $X_{iM,n}$. $X_{iE,n}$ comprises five energy goods $X^{E}_{ij,n}$, and $X_{iM,n}$ is composed of seven non-energy goods $X^{M}_{ij,n}$. Given this production technology, the producer problem can be formulated as:

$$\max \quad V_{i,n}(t) = \int_t^{\infty} \exp\left[-\int_t^{s} r_n(s')\cdot ds'\right]\cdot \Pi_{i,n}(s)\cdot ds \tag{5.22}$$

$$\begin{aligned} \text{s.t. } \Pi_{i,n}(t) = {} & (1-\tau_{Q,n})\cdot P_{i,n}(t)\cdot Q_{i,n}(t) - P_{iL,n}(t)\cdot X_{iL,n}(t) - (1+\tau_{C,n})\cdot P_{iE,n}(t)\cdot X_{iE,n}(t) \\ & - P_{iM,n}(t)\cdot X_{iM,n}(t) - (1-\tau_{I,n})\cdot P_{iI,n}(t)\cdot I_{i,n}(t) - (1-\tau_{R,n})\cdot P_{iR,n}(t)\cdot R_{i,n}(t) \end{aligned} \tag{5.23}$$

$$\dot{K}_{i,n}(t) = J_{i,n}(t) - \delta_{K,n}\cdot K_{i,n}(t) \tag{5.24}$$

$$I_{i,n}(t) = \varphi(J_{i,n}(t), K_{i,n}(t)) = J_{i,n}(t)\cdot\left[1+\frac{\psi}{2}\cdot\frac{J_{i,n}(t)}{K_{i,n}(t)}\right] \tag{5.25}$$

$$\dot{H}_{i,n}(t) = \underbrace{\eta\cdot R_{i,n}(t)^{\alpha}\cdot H_{i,n}(t)^{\beta} - \delta_{H,n}\cdot H_{i,n}(t)}_{\text{Indigenous innovation}} + \underbrace{\gamma_{i,n}(t)\cdot\left[R^{T}_{i,n}(t)+R^{F}_{i,n}(t)+R^{D}_{i,n}(t)\right]}_{\text{International technology diffusion}} \tag{5.26}$$

where the objective of the producer in sector i, country n is to choose the inputs of labor $X_{iL,n}$, energy $X_{iE,n}$, material $X_{iM,n}$, capital investment $I_{i,n}$, and R&D investment $R_{i,n}$ to maximize an intertemporal profit stream $V_{i,n}$, subject to the technology constraints. In Eq. (5.22), $V_{i,n}$ is expressed as the discounted present value of future profit streams from time t to an infinite future. In Eq. (5.23), current profit flow Π_i equals output revenues minus input costs, with $\tau_{Qn}, \tau_{Cn}, \tau_{In}, \tau_{Rn}$ being corporate income tax, carbon tax on fossil energy inputs, investment tax credit, and R&D tax credit, respectively.

Eq. (5.24) specifies the law of motion of physical capital stock $K_{i,n}$, its accumulation depends on fixed capital investment $J_{i,n}$ and the rate of capital depreciation $\delta_{K,n}$. Eq. (5.25) models the capital investment process that is subject to imperfect capital mobility and investment adjustment cost (Goulder and Schneider, 1999; McKibbin and Wilcoxen, 1999).

Eq. (5.26) is the *innovation possibility frontier (IPF)* that explicitly represents the process of knowledge creation, where accumulation of domestic knowledge stock $\dot{H}_{i,n}$ are driven by dual forces: (1) Indigenous innovation: Both indigenous R&D investment ($R_{i,n}$) and existing knowledge stock ($H_{i,n}$) contribute to in-house knowledge creation. η denotes the efficiency of knowledge creation. $\delta_{H,n}$ is the rate of knowledge obsolescence. The conditions $0<\eta<1$, $0<\alpha+\beta<1$ implies diminishing returns to R&D in innovation; (2) International technology diffusion: Foreign knowledge diffusion occurs through three channels: imports ($R^{T}_{i,n}$), FDI ($R^{F}_{i,n}$), and disembodied spillovers ($R^{D}_{i,n}$). A fraction of diffused knowledge is absorbed for building domestic knowledge according to local knowledge absorption capacity ($\gamma_{i,n}$).

5.3.3 International Technology Diffusion

As described in Section 5.2, the purpose of international R&D coordination is to internalize the positive externality resulting from cross-country technology diffusion (TD). This section thus aims to articulate how to model the various channels of international TD.

Drawing on the insights of Griliches (1979) on two types of R&D spillovers, I identify two principal mechanisms of foreign TD: 1) Embodied knowledge diffusion through indirectly employing knowledge-embodied intermediate and capital goods; 2) Disembodied knowledge diffusion through directly learning disembodied knowledge spillover.

Embodied knowledge diffusion occurs when domestic firms indirectly benefit from external innovation by using knowledge-embodied foreign intermediate commodity (via import) or capital goods (via FDI). Embodied TD has its theoretical and empirical origins in the work by Coe and Helpman (1995), indicating that international TD should be embodied in the flows of physical commodity transactions through the channels of international trade and investment.

In parallel, disembodied knowledge diffusion involves direct learning and absorption of the disembodied forms of technologies (e.g., formulas, blueprints, patents), not necessarily linking to economic transactions of tangible physical goods. Disembodied TD is rooted in the seminal works by Rivera-Batiz and Romer (1991) that suggests the key role of disembodied knowledge spillover externality in the process of international TD.

To describe both TD mechanisms, Sections 5.3.3.1-5.3.3.3 provide a framework to model three channels, including: TD embodied in trade, TD embodied in FDI, and disembodied TD. Moreover, while knowledge can diffuse from abroad through these three channels, the efficiencies of assimilating the diffused knowledge of the recipient countries are determined by local knowledge absorptive capacity, which will be described in Section 5.3.3.4.

5.3.3.1 Technology Diffusion Embodied in Trade

TD embodied in trade refers to the mechanism where domestic firms benefit from external knowledge by using knowledge-embodied foreign intermediate commodity via import.[15] In other words, if we think of commodity import as a vehicle of TD, then foreign knowledge is embodied in intermediate commodity imports, with embodied knowledge being assimilated by the recipient country for domestic knowledge accumulation. To represent this mechanism, we model China's import flows in line with the Armington structure, with the Armington composite of intermediate goods modeled as a CES aggregate of domestically-produced and imported component of that commodity as:

$$X_{ij,n}(t) = \left[X^{D}_{ij,n}(t)^{\frac{\sigma_j^T - 1}{\sigma_j^T}} + X^{T}_{ij,n}(t)^{\frac{\sigma_j^T - 1}{\sigma_j^T}} \right]^{\frac{\sigma_j^T}{\sigma_j^T - 1}} \tag{5.27}$$

where $X_{ij,n}$ is the composite of intermediate input goods j used by production sector i in region n, expressed as a CES aggregate of domestic $X^{D}_{ij,n}$ and imported component $X^{T}_{ij,n}$ of that intermediate goods. Substitution between domestic and import component is governed

[15] Empirical evidences of this TD pattern is recorded in the pioneering work by Coe and Helpman (1995) who found a statistically significant effect of bilateral trade on international TD. Other empirical studies also find the significant and positive link between a country's factor productivity and knowledge created by its trading partners (e.g., Coe et al., 1997; Keller, 1998; Xu and Wang, 1999; Pavcnik, 2002; Madsen, 2007; Eaton and Kortum, 2001, 2002; Amiti and Konings, 2007; Acharya and Keller, 2009).

by the Armington elasticity σ_j^T. Within this multi-country model that distinguishes multiple sources of imports, the import composite is further modeled as a CES aggregate of imports from all sources of foreign exporting regions as:

$$X_{ij,n}^T(t) = \left[\sum_r X_{ij,nr}^T(t)^{\frac{\sigma_j^{TT}-1}{\sigma_j^{TT}}}\right]^{\frac{\sigma_j^{TT}}{\sigma_j^{TT}-1}} \tag{5.28}$$

where $X_{ij,nr}^T$ is the import of intermediate input goods j into sector i in destination region n from source region r. Substitution among foreign regions is governed by the elasticity σ_j^{TT}.

By solving the producer problem we can characterize the import of intermediate input commodity j into destination region n from source region r ($X_{ij,nr}^T$) as:

$$X_{ij,nr}^T(t) = \left[\frac{P_{j,n}^T(t)}{P_{j,r}(t)\cdot(1+\tau_j^T)}\right]^{\sigma_j^{TT}} \cdot X_{ij,n}^T(t) = \left[\frac{P_{j,n}^T(t)}{P_{j,r}(t)\cdot(1+\tau_j^T)}\right]^{\sigma_j^{TT}} \cdot \left[\frac{P_{j,n}(t)}{P_{j,n}^T(t)}\right]^{\sigma_i^T} \cdot X_{ij,n}(t) \tag{5.29}$$

where $P_{j,n}$ is the market price of intermediate goods composite j in destination country n. $P_{j,n}^T$ is the ideal price index of imported component of that intermediate goods j. $P_{j,r}$ is the price of intermediate goods j in source country r. τ_j^T is the rate of import tariff imposed on commodity j. $P_{j,r}\cdot(1+\tau_j^T)$ is the import price of commodity j in destination region n from source country r.

As argued above, both import flows and knowledge embodiment intensity determine the amount of knowledge diffused through trade. So far Eq. (5.29) has estimated the imports of intermediate commodity from source to destination countries. We further introduce the other factor: intensity of knowledge embodied in imports, which is the amount of knowledge that is embodied in each unit of import flows. In line with the embodied technology hypothesis, this intensity can be estimated as:[16]

$$RI_{j,r}^T(t) = \theta^T \cdot \frac{R_{j,r}(t)}{Y_{j,r}(t)} \tag{5.30}$$

[16] *"Embodied technology hypothesis"* claims that intangible knowledge has to be embodied in specific physical products in order to embody economically useful characteristics (Schmookler, 1966; Terleckyj, 1974; Scherer, 1982; Papaconstantinou et al., 1998; Hauknes and Knell, 2009).

where $RI^{T}_{j,r}$ denotes the intensity of knowledge embodied in intermediate goods j imported from source country r. This intensity is measured as a ratio between R&D expenditure ($R_{j,r}$) and production output ($Y_{j,r}$) in source country r. θ^{T} is an exogenous parameter that indicates foreign restrictions on exporting knowledge-intensive hi-tech products.

Given the two determinants of TD through trade, we model the diffusion of knowledge embodied in trade as a product of import flows ($X^{T}_{ij,nr}$) and embodied knowledge intensity ($RI^{T}_{j,r}$) as:

$$R^{T}_{ij,nr}(t) = X^{T}_{ij,nr}(t) \cdot RI^{T}_{j,r}(t) \tag{5.31}$$

where $R^{T}_{ij,nr}$ denotes knowledge embodied in the import of intermediate commodity j from source country r into the sector i of destination country n. Next, I estimate the total amount of knowledge embodied in import flows as follows:

$$R^{T}_{i,n}(t) = \sum_{j} R^{T}_{ij,n}(t) = \sum_{j}\sum_{r} R^{T}_{ij,nr}(t) \tag{5.32}$$

where, by summing over foreign countries r and intermediate input varieties j, I estimate the total amount of knowledge embodied in imports into destination country n ($R^{T}_{i,n}$), which is incorporated into the *IPF* in Eq. (5.26) to represent embodied knowledge diffusion via trade.

5.3.3.2 Technology Diffusion Embodied in FDI

TD embodied in FDI refers to the mechanism where domestic firms benefit from external knowledge by using knowledge-embodied foreign capital goods via FDI. In this sense, if we think of FDI as a vehicle of TD, then foreign knowledge is embodied in foreign invested capital, with the embodied knowledge absorbed by the recipient country for knowledge accumulation.[17] To describe this mechanism, we assume that capitals installed by domestic and foreign investors are imperfect substitutes in physical capital formation (Markusen, 2002;

[17] Empirical evidence for this kind of TD is recorded in the work by Blomström and Persson (1983) who found a statistically significant influence of FDI inflows on international TD. Other empirical studies also suggest that host countries benefit from knowledge diffused from MNC foreign affiliates, with FDI being a robust diffusion channel (e.g., Haddad and Harrison, 1993; Aitken and Harrison, 1999; Keller and Yeaple, 2009; Rodriguez-Clare, 1996; Blomström and Kokko, 1998; Javorcik, 2004; Lin and Saggi, 2007; Haskel et al., 2007; Blalock and Gertler, 2008).

Lejour et al., 2008). Physical capitals invested in China are thus modeled as a CES aggregate of domestic and foreign components of that capital goods as:

$$I_{i,n}(t) = \left[I_{i,n}^{D}(t)^{\frac{\sigma_I^F - 1}{\sigma_I^F}} + I_{i,n}^{F}(t)^{\frac{\sigma_I^F - 1}{\sigma_I^F}} \right]^{\frac{\sigma_I^F}{\sigma_I^F - 1}} \tag{5.33}$$

where $I_{i,n}$ is the composite of physical capital invested in sector i of destination country n, expressed as a CES aggregate of domestic I_i^D and foreign components I_i^F of that capital goods composite. Substitution between the two components is governed by the elasticity σ_I^F, indicating joint venture requirement in foreign investments entry. Within the multi-region model that distinguishes multiple FDI sources, the composite of foreign-invested capital is further modeled as a CES aggregate of FDI from all foreign source countries as:

$$I_{i,n}^{F}(t) = \left[\sum_r I_{i,nr}^{F}(t)^{\frac{\sigma_I^{FF} - 1}{\sigma_I^{FF}}} \right]^{\frac{\sigma_I^{FF}}{\sigma_I^{FF} - 1}} \tag{5.34}$$

where $I_{i,nr}^F$ is the FDI inflows from foreign origin country r into sector i in the recipient country n. Substitution between foreign countries is governed by the CES elasticity (σ_I^{FF}).

By solving the producer problem, we can characterize the levels of FDI invested by each source country r in destination country n ($I_{i,nr}^F$) as:

$$I_{i,nr}^{F}(t) = \left[\frac{P_{I,n}^F(t)}{P_{I,r}(t)\cdot(1+\tau_I^F)} \right]^{\sigma_I^{FF}} \cdot I_{i,n}^F(t) = \left[\frac{P_{I,n}^F(t)}{P_{I,r}(t)\cdot(1+\tau_I^F)} \right]^{\sigma_I^{FF}} \cdot \left[\frac{P_{I,n}(t)}{P_{I,n}^F(t)} \right]^{\sigma_I^F} \cdot I_{i,n}(t) \tag{5.35}$$

where $P_{I,n}$ is the price of capital good in destination country n. $P_{I,n}^F$ is the ideal price index of FDI composite in destination country n. $P_{I,r}$ is the price of capital goods invested by source country r. τ_I^F is the rate of preferable tax (fiscal incentive) offered to MNC affiliates. $P_{I,r}(t)\cdot(1+\tau_I^F)$ is the after-tax price of capital goods invested by foreign source country r.

As argued above, both the level of FDI and knowledge embodiment intensity determine the amount of knowledge diffused through FDI. So far the level of FDI has been estimated by Eq. (5.35), I further model the knowledge intensity of FDI (the amount of knowledge embodied in each unit of FDI inflows) as follows:

$$RI^F_{i,r}(t) = \theta^F \cdot \frac{R_{i,r}(t)}{Y_{i,r}(t)} \tag{5.36}$$

where $RI^F_{i,r}$ denotes the intensity of knowledge embodied in physical capital goods invested by source country r, measured as a ratio between R&D expenditure ($R_{i,r}$) and production output ($Y_{i,r}$) in source country r. θ^F is an exogenous parameter indicating foreign restriction on transferring technologies through FDI.

Given the two determinants of TD through FDI, we model the diffusion of knowledge embodied in FDI as a product of FDI flows ($I^F_{i,nr}$) and embodied knowledge intensity ($RI^F_{i,r}$) as:

$$R^F_{i,nr}(t) = I^F_{i,nr}(t) \cdot RI^F_{i,r}(t) \tag{5.37}$$

where $R^F_{i,nr}$ denotes knowledge embodied in FDI in sector i from foreign source country r. By summing over source countries r, I estimate knowledge embodied in FDI as follows:

$$R^F_{i,n}(t) = \sum_r R^F_{i,nr}(t) \tag{5.38}$$

where $R^F_{i,n}$ denotes the total amount of knowledge that is embodied in FDI into sector i in destination country n, which is added into the *IPF* in Eq. (5.26) to represent the embodied knowledge diffusion through the channel of international investment.

5.3.3.3 Disembodied Technology Diffusion

Disembodied TD occurs when disembodied pure knowledge (as a public good) spill over from technology frontier countries to the laggards due to an imperfect appropriability of knowledge, which does not necessarily link to the economic transactions of physical goods. Learning and absorption of disembodied knowledge thus favors innovation in places different from where originally created (Romer, 1990; Rivera-Batiz and Romer, 1991; Jaffe and Trajtenberg, 1998; Eaton and Kortum, 1999; Lee, 2006).

In this context, I draw on the insights of Bosetti et al. (2008) and postulate that each individual region is exposed to an international disembodied knowledge pool created by the whole set of world regions. On the one hand, due to the path dependence of innovation and technology differentiation, individual regions create heterogeneous knowledge specific to local socio-technological circumstances.[18] As a result, the international knowledge pool is constituted by the overall amount of R&D invested by individual regions. On the other hand, when innovation paths tend to diverge across regions, the difference between region-specific R&D and world-wide R&D constitutes the potential source of foreign knowledge spillover that can be absorbed for building domestic knowledge. Thus, the disembodied knowledge that may spill over into a given region n can be modeled as

$$R_{i,n}^{D}(t) = \theta^{D} \cdot \sum_{r} R_{i,r}(t) - R_{i,n}(t) \tag{5.39}$$

where $\sum_r R_{i,r}$ is the global R&D as a sum of region-specific R&D ($R_{i,r}$) over all individual regions r. $R_{i,n}$ is indigenous R&D invested by the considered region n. The gap between world-wide R&D and region-specific R&D thus constitutes foreign disembodied knowledge that may spill over to the region n. θ^D is an exogenous parameter indicating the externality of disembodied knowledge spillovers, of which the value is regulated by patent policy in foreign countries. $R_{i,n}^D$ is then incorporated into *IPF* in Eq. (5.26) to represent international knowledge diffusion through the disembodied channel.

5.3.3.4 Knowledge Absorptive Capacity

So far we have captured all three channels of international TD, the diffused knowledge, however, are not the "manna from heaven" that indiscriminately falls on the host country, only a fraction can be effectively absorbed according to local socio-technological condition.[19] The benefits of knowledge diffusion can be realized only if the recipient country builds an indigenous capacity of knowledge absorption.

Basically, knowledge absorptive capacity reflects the technology distance of one region relative to the global technology frontier, which is measured as the ratio of R&D investment

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[18] This coincides with the so-called path dependence of innovation. That is, technology progress within each technology frontier country tends to follow a specific trajectory that is embedded in local socio-technological context, creating differentiated and heterogeneous technology varieties (Nelson, 1993; Rosenberg, 1994)..

[19] This "localness" is reflected by the mismatch between transferred technology and locality in developing countries. For an articulation on the inappropriateness of technologies and its effect on productivity difference across nations, see Acemoglu (2009).

between one specific region ($R_{i,n}$) and the whole world ($\sum_r R_{i,r}$) as follows:

$$\gamma_{i,n}(t) = \frac{R_{i,n}(t)}{\sum_r R_{i,r}(t)} \tag{5.40}$$

where the lower the value of the ratio for a given region n, the further its technology distance relative to the global frontier. With a backward position in the global technology ladder, this region has weaker indigenous capacity to absorb external knowledge. Put differently, a lack of R&D commitment translates into a weaker indigenous capacity of knowledge absorption, which further becomes a barrier to assimilate knowledge diffused from abroad.

5.3.4 International R&D Coordination

So far international knowledge diffusions via various channels have been fully described in the numerical model, based on which I attempt to articulate the mechanism of international R&D coordination in this section. In explicit, two alternative equilibria will be considered: non-coordinated innovation equilibrium (in Section 5.3.4.1) and coordinated innovation equilibrium (in Section 5.3.4.2). The numerical model will be simulated in Section 5.4 to quantitatively examine economic and environmental performances in both innovation equilibria, so that the effect of international R&D coordination can be captured.

5.3.4.1 Non-coordinated Innovation Equilibrium

In a non-cooperative innovation equilibrium, each country chooses the levels of indigenous R&D spending independently, with the purpose of advancing country-specific innovation and TC. This unilateral R&D plan takes no account of the positive effect of cross-country knowledge diffusions that favor innovation and TC in other countries. In this case, the single-country producer problem (see Eqs. (5.22)-(5.26)) can be solved to characterize the behavior of R&D spending by any individual country n in a decentralized non-coordinated innovation equilibrium as:

$$(1-\tau_{R,n})\cdot P_{iR,n}(t) = \lambda_{iH,n}(t)\cdot\left[a\cdot\eta\cdot R_{i,n}(t)^{a-1}\cdot H_{i,n}(t)^{\beta} + \frac{\partial\left[\gamma_{i,n}(t)\cdot\left(R^{T}_{i,n}(t)+R^{F}_{i,n}(t)+R^{D}_{i,n}(t)\right)\right]}{\partial R_{i,n}(t)}\right] \tag{5.41}$$

where Eq. (5.41) is the optimality condition that characterizes the levels of indigenous R&D

investment undertaken by country n ($R_{i,n}$). It instructs the R&D investment of that country to reach a level where the marginal cost (LHS) is equal to the marginal benefit (RHS). The marginal cost comes from expenditures on purchasing an extra unit of R&D goods. The marginal benefits include the shadow price of knowledge capitals λ_{iH} and innovation possibility gain. In particular, the innovation possibility gains from R&D investment can be harvested from two sources: Indigenous R&D not only directly create in-house knowledge, but also enhance indigenous capacity to assimilate foreign knowledge diffusion - the dual faces of R&D in innovation (Cohen and Levinthal, 1989; Keller, 1996; Griffith et al., 2000).

Note that, the purpose of R&D investment is for domestic innovation possibility gains that include twofold: 1) creation of in-house new knowledge; 2) improvement of indigenous capacity to absorb foreign knowledge diffusion. However, this process of R&D decision pays no attention to the positive externality of technology: knowledge created by indigenous R&D in one country may spill over into other countries to favor innovation there. As shown later, it is the underestimation of the beneficial effect of indigenous R&D on foreign innovation that makes individual countries choose R&D spending levels that are comparatively lower.

5.3.4.2 Coordinated Innovation Equilibrium

In the coordinated innovation equilibrium, the levels of R&D spending set by individual countries are coordinated by an international coordinating body which enforces multilateral technology cooperation. In setting the country composition of global R&D spending, the coordinating body aims for an internalization of the technology externality resulting from cross-country reciprocal knowledge diffusion, which can be characterized as:

$$
\begin{aligned}
(1-\tau_{R,n})\cdot P_{iR,n}(t) = \lambda_{iH,n}(t)\cdot&\left[a\cdot\eta\cdot R_{i,n}(t)^{a-1}\cdot H_{i,n}(t)^{\beta}+\frac{\partial\left[\gamma_{i,n}(t)\cdot\left(R_{i,n}^{T}(t)+R_{i,n}^{F}(t)+R_{i,n}^{D}(t)\right)\right]}{\partial R_{i,n}(t)}\right] \\
&\underbrace{+\sum\nolimits_{r\neq n}\lambda_{iH,r}(t)\cdot\left[\frac{\partial\left[\gamma_{i,r}(t)\cdot\left(R_{i,r}^{T}(t)+R_{i,r}^{F}(t)+R_{i,r}^{D}(t)\right)\right]}{\partial R_{i,n}(t)}\right]}_{\text{R\&D spillover from country n to all other countries } r\neq n}
\end{aligned}
\tag{5.42}
$$

where in the optimality condition, the coordinating body instructs any individual country n to spend R&D expenditure levels where the LHS marginal cost equals to the RHS marginal benefit. By comparing the optimality conditions between Eq. (5.42) and Eq. (5.41), I find that in the coordinated innovation equilibrium, the coordinating body would allow for both within-country and cross-country benefits of R&D investment: 1) Within-country benefit: indigenous R&D directly benefits knowledge creation in the innovating country (the first term on the RHS), which is the same as in the non-coordinated case; 2) Cross-country benefit: indigenous R&D also generates cross-country knowledge diffusion that favors innovation in other countries (the second term on the RHS), which is the new feature in the coordinated innovation.

Turn to the deep structure of the cross-country benefit resulting from international knowledge diffusion, I rewrite the second term on the RHS in Eq. (5.42) as:

$$\begin{aligned}&\sum\nolimits_{r\neq n}\lambda_{iH,r}(t)\cdot\left[\frac{\partial\left[\gamma_{i,r}(t)\cdot(R^T_{i,r}(t)+R^F_{i,r}(t)+R^D_{i,r}(t))\right]}{\partial R_{i,n}(t)}\right]\\&=\sum\nolimits_{r\neq n}\lambda_{iH,r}(t)\cdot\left[(R^T_{i,r}(t)+R^F_{i,r}(t)+R^D_{i,r}(t))\cdot\frac{\partial\gamma_{i,r}(t)}{\partial R_{i,n}(t)}+\gamma_{i,r}(t)\cdot\frac{\partial\left(R^T_{i,r}(t)+R^F_{i,r}(t)+R^D_{i,r}(t)\right)}{\partial R_{i,n}(t)}\right]\end{aligned}\tag{5.43}$$

where $\partial\gamma_{i,r}/\partial R_{i,n}$ denotes the effect of indigenous R&D in a given country n on knowledge absorptive capacity of another country $r\neq n$. Recall that, knowledge absorptive capacity is modeled as a ratio of country-specific R&D relative to global total R&D, $\gamma_{i,r}=R_{i,r}/\sum_n R_{i,n}$, with the derivative $\partial\gamma_{i,r}/\partial R_{i,n}=-R_{i,r}\cdot(\sum_n R_{i,n})^{-2}$. Consider that, the global technology frontier is constituted by a whole set of world countries rather than a single one country, R&D invested by any single country is thus sufficiently small relative to global totals, with $R_{i,r}\ll\sum_n R_{i,n}\ll(\sum_n R_{i,n})^2$ and $\partial\gamma_{i,r}/\partial R_{i,n}\approx 0$. The Eq. (5.43) can hereby be simplified as:

$$\begin{aligned}&\sum\nolimits_{r\neq n}\lambda_{iH,r}(t)\cdot\left[\frac{\partial\left[\gamma_{i,r}(t)\cdot(R^T_{i,r}(t)+R^F_{i,r}(t)+R^D_{i,r}(t))\right]}{\partial R_{i,n}(t)}\right]\\&=\sum\nolimits_{r\neq n}\lambda_{iH,r}(t)\cdot\gamma_{i,r}(t)\cdot\frac{\partial(R^T_{i,r}(t)+R^F_{i,r}(t)+R^D_{i,r}(t))}{\partial R_{i,n}(t)}\end{aligned}\tag{5.44}$$

where $\partial(R^T_{i,r}+R^F_{i,r}+R^D_{i,r})/\partial R_{i,n}$ represents the effect of indigenous R&D investment on international knowledge diffusion. That is, the amount of additional knowledge diffusion into another country r (via trade, FDI, and disembodied spillover) from investing an extra unit of indigenous R&D in country n. The deep structure of Eq. (5.44) can be expressed as:

$$
\begin{aligned}
&\sum_{r\neq n}\lambda_{iH,r}(t)\cdot\left[\frac{\partial\left[\gamma_{i,r}(t)\cdot\left(R^{T}_{i,r}(t)+R^{F}_{i,r}(t)+R^{D}_{i,r}(t)\right)\right]}{\partial R_{i,n}(t)}\right]\\
&=\sum_{r\neq n}\lambda_{iH,r}(t)\cdot\gamma_{i,r}(t)\cdot\frac{\partial\left(R^{T}_{i,r}(t)+R^{F}_{i,r}(t)+R^{D}_{i,r}(t)\right)}{\partial R_{i,n}(t)}\\
&=\sum_{r\neq n}\lambda_{iH,r}(t)\cdot\gamma_{i,r}(t)\cdot\left[\theta^{T}\cdot\frac{X^{T}_{i,nr}(t)}{Y_{i,n}(t)}+\theta^{F}\cdot\frac{I^{F}_{i,nr}(t)}{Y_{i,n}(t)}+\theta^{D}\right]
\end{aligned}
\tag{5.45}
$$

where $\theta^{T}\cdot X^{T}_{i,nr}/Y_{i,n}$, $\theta^{F}\cdot I^{F}_{i,nr}/Y_{i,n}$ denote the effect of indigenous R&D in one country n on embodied knowledge diffusion into another country $r\neq n$ through trade and FDI, respectively.[20] The ratio of export (from source country n to destination country r) relative to production output in the source country n, $X^{T}_{i,nr}/Y_{i,n}$, represents the intensity of commodity export from source to destination country. It suggests that a higher level of export intensity and trade linkage is more likely to create cross-country knowledge diffusions through the channel of trade. Meanwhile, $I^{F}_{i,nr}/Y_{i,n}$ denotes the intensity of foreign capital investment by source country n into destination country r, suggesting that a higher level of international investment linkage tends to create more knowledge diffusions through the channel of FDI. Parameters θ^{T},θ^{F} denote restrictions of technology transfer that govern the intensity of knowledge embodied in international trade and FDI. Finally, parameter θ^{D} denotes the effect of indigenous R&D on disembodied knowledge spillover, which is normally regulated by patent policy. A lax intellectual property protection system is more likely to generate the externality of disembodied pure knowledge spillover.

I thus find that, as compared to the non-coordinated case, innovation coordination can create an additional benefit of R&D investment: cross-country knowledge diffusion through the embodied and disembodied channels. According to the optimality conditions that characterize R&D spending (see Eqs. (5.41)-(5.42)), we further find that, with the same levels of marginal cost, an innovation equilibrium that creates a higher level of marginal benefit would have more R&D investment. Therefore, the coordinated innovation would stimulate a higher level of R&D invested by individual countries and collective provision of knowledge.

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20 Commonly, knowledge diffusion is dealt with as an externality that can't be anticipated by private agents in a decentralized context. However, while this view may be true for disembodied knowledge spillover, it is debatable to embodied technology diffusion that links economic transaction of physical products. Empirical studies have suggested that, given the significantly positive link between productivity gain and international trade (also FDI) foresighted private agents in their decision making will take into account this potential technology spillover when trading their superior technology in foreign markets (e.g., Dechezlepretre et al., 2009).

5.4 Results and Discussions

5.4.1 Alternative Scenario Settings

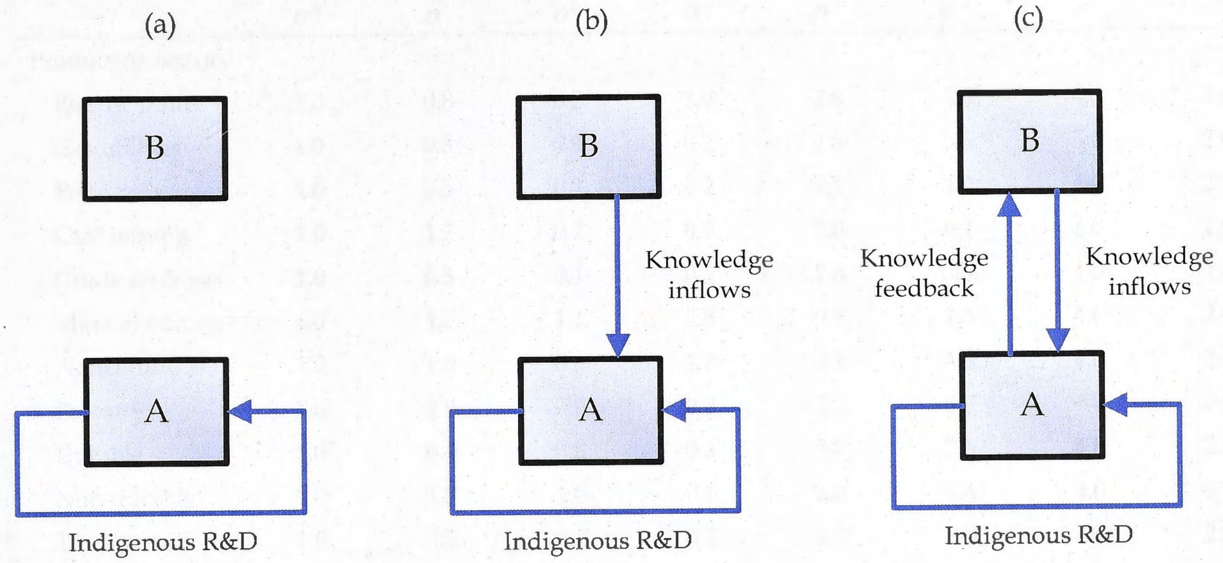
Recall that, the primary purpose of this research is to show the importance of international R&D coordination as a technology strategy to global climate mitigation. To achieve this goal, I simulate the numerical model under three innovation scenarios (see Fig. 5.3), including:

(a) Indigenous innovation scenario: TC in any individual country (say A) only relies on indigenous R&D as the single source of knowledge creation, ignoring the potential role of foreign knowledge inflows from other countries (say B) to complement indigenous R&D for building domestic knowledge stock.

(b) Non-coordinated innovation scenario: TC in any individual country A relies on both indigenous R&D and foreign knowledge diffusion as dual sources of knowledge creation. In setting the R&D spending levels, country A only considers enhancing indigenous capacity to assimilate foreign knowledge inflows (from B to A), taking no account of providing beneficial knowledge feedback (from A to B). Since the externality of knowledge spillover is not fully internalized, R&D investments by individual countries are non-coordinated - a non- coordinated innovation equilibrium (see Section 5.3.4.1).

(c) Coordinated innovation scenario: In setting the R&D spending levels, country A not only considers enhancing indigenous capacity of absorbing foreign knowledge inflows (from B to A), but also is instructed by an international coordinating body to provide beneficial knowledge feedback (from A to B). Since the externality of knowledge spillover is fully internalized, R&D investments by individual countries are coordinated – a coordinated innovation equilibrium (see Section 5.3.4.2).

Figure 5.3: Settings of three alternative innovation scenarios



Note: (a) Indigenous innovation scenario, where individual regions are treated as an isolated island with ouly indigenous R&D; (b) Non-coordinated innovation scenario, where individual regions can absorb unidirectional knowledge inflows; (c) Coordinated innovation scenario, where individual regions are instructed to provide beneficial knowledge feedback to other regions

Intuitively, comparison between Scenario (b) and (a) reflects foreign knowledge inflow and its effect on stimulating indigenous R&D investment. That is, indigenous innovation can be induced by foreign knowledge inflows, because absorption of foreign diffused knowledge requires building local knowledge absorptive capacity through indigenous R&D investment according to the theory of the dual faces of indigenous R&D in innovation. In addition, comparison between Scenario (c) and (b) reflects international R&D coordination and its effect on boosting indigenous R&D of individual countries. That is, by internalizing the positive externality of cross-country knowledge diffusion, multilateral R&D coordination can stimulate country-specific R&D commitment and global collective efforts of innovation.

To quantitatively examine these arguments, I simulate the numerical model following the implementation and calibration procedure as described in Chapter 4. Various parameters used in the model are listed in Tabs. 5.1-5.2. The CGE modeling software GEMPACK is used to solve the numerical model and simulate the three aforementioned innovation scenarios, to which I now turn.

Table 5.1: Substitution elasticity

	σ^{Q}	σ^{Z}	σ^{E}	σ^{M}	σ^{T}	σ^{TT}	σ^{F}	σ^{FF}
Production sectors								
Electric utility	1.0	0.8	0.2	1.0	2.8	5.6	4.0	2.0
Gas utilities	1.0	0.8	0.9	0.2	2.8	5.6	4.0	2.0
Petro refining	1.0	0.5	0.2	0.2	2.1	4.2	4.0	2.0
Coal mining	1.0	1.7	0.2	0.5	3.0	6.1	4.0	2.0
Crude oil & gas	1.0	0.5	0.1	0.2	7.6	14.4	4.0	2.0
Mineral mining	1.0	1.0	1.1	2.8	0.9	1.8	4.0	2.0
Agriculture	1.0	1.3	0.6	1.7	2.4	4.8	4.0	2.0
Forestry	1.0	0.9	0.9	0.2	3.2	6.7	4.0	2.0
Durable	1.0	0.4	0.8	0.2	3.7	7.6	4.0	2.0
Non-durable	1.0	1.0	1.0	0.1	3.0	6.4	4.0	2.0
Transportation	1.0	0.5	0.2	0.2	1.9	3.8	4.0	2.0
Services	1.0	0.3	0.3	3.0	1.9	3.8	4.0	2.0

σ^{Q}: Elasticity of substitution between knowledge input and physical input composite.

σ^{Z}: Elasticity of substitution among the physical inputs of capital, labor, energy, and material.

σ^{E}: Elasticity of substitution among intermediate energy goods.

σ^{M}: Elasticity of substitution among intermediate material goods.

σ^{T}: Armington elasticity of substitution between domestic and imported variety of intermediate commodities.

σ^{TT}: CES elasticity of substitution for regional composition of import bundles.

σ^{F}: CES elasticity of substitution between domestic and foreign-invested physical capital goods.

σ^{FF}: CES elasticity of substitution for regional composition of FDI.

Note: Physical capital goods invested in industrial sectors are assumed to have a substantial degree of homogeneity,I hereby impose a restriction that the substitution elasticities of physical capital investment are equal across sectors. I also assume that substitution elasticities within individual sectors are equal across world regions. This assumption does not mean, however, that the elasticities are the same across sectors within a given world region.

Source: Goulder and Schneider (1999), McKibbin and Wilcoxen (1999), Sue Wing (2001; 2003), Löschel and Otto (2009), Narayanan and Walmsley (2008), Springer (1998), Mai (2005), Lejour et al. (2008).

Table 5.2: Parameter values

	USA	EUW	ROECD	CHN	BRIS	ROW
τ_Q	0.40	0.30	0.30	0.25	0.30	0.15
τ_I	0.12	0.15	0.15	0.20	0.15	0.20
τ_R	0.06	0.08	0.10	0.10	0.10	0.10
α	0.18	0.18	0.18	0.18	0.18	0.18
β	0.53	0.53	0.53	0.53	0.53	0.53
η	0.02	0.02	0.02	0.02	0.02	0.02
r	0.03	0.03	0.05	0.01	0.02	0.05
δ_K	0.05	0.05	0.05	0.05	0.05	0.05
δ_H	0.1	0.1	0.1	0.1	0.1	0.1
ψ	4	4	4	4	4	4

τ_Q : Corporate profit tax rate

τ_I : Investment tax credit

τ_R : R&D tax credit

α : Elasticity of knowledge creation to R&D investment

β : Elasticity of knowledge creation to existing knowledge stock

η : Efficiency of knowledge creation

r : Real interest rate

δ_K : Depreciation rate of physical capital

δ_H : Depreciation rate of knowledge capital

Ψ : Investment adjustment cost coefficient

Source: Goulder and Schneider (1999), McKibbin and Wilcoxen (1999), Popp (2004), Bosetti et al. (2008), OECD (2010), World Bank (2011).

5.4.2 Technology Coordination without Emissions Control Policies

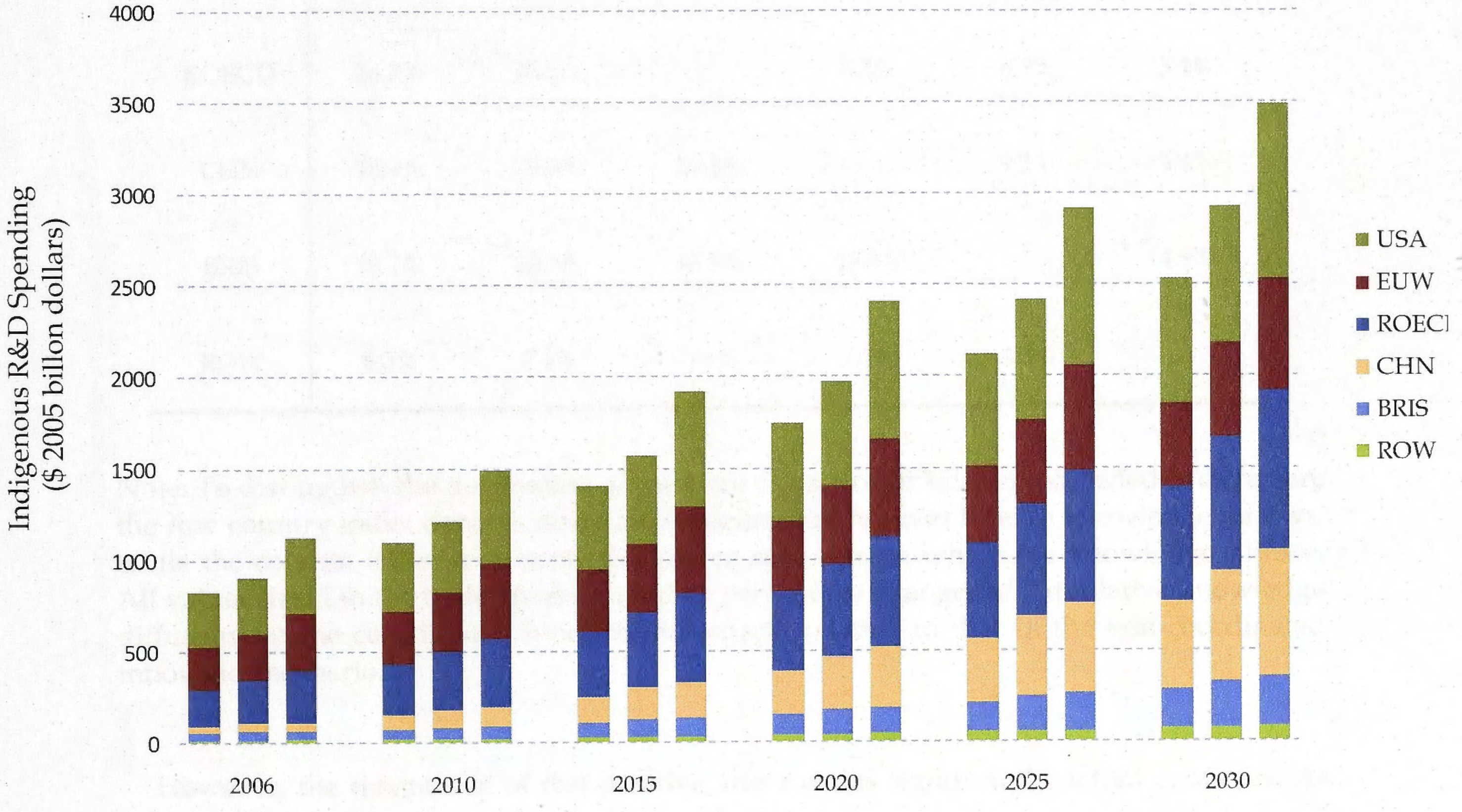
In this section, I firstly examine the effect of international R&D coordination in the absence of emissions control policies. The analysis in the next section will give insights into how R&D coordination can synergize with emission control policies to help lower climate mitigation cost. As Fig. 5.4 reveals, the temporal profile of global R&D spending is on a rising trend in all three innovation scenarios. The growing global R&D are spread across individual nations, with the OECD accounting for the bulk (80%) of total spending in the short run (2005-2020). This share, however, is likely to fall in the long run (2020-2030), which is largely offset by the share gains of the emerging economies (20-30% of global R&D by 2030).

It is also notable that among the three innovation scenarios, coordinated innovation creates the highest levels of R&D spending (both worldwide and country-specific), followed by non-coordinated innovation, and finally indigenous innovation. The reasons are two-fold. Firstly, non-coordinated innovation allows for the potential of foreign knowledge inflows to complement indigenous R&D in innovation. To absorb the diffused knowledge, individual countries would enhance indigenous R&D for building local knowledge absorptive capacity. Accordingly, a higher level of R&D will be stimulated in the non-coordinated innovation scenario as compared to the indigenous innovation scenario.

Secondly, the coordinated innovation explicitly considers an internalization of positive technology externality, where individual countries are instructed to undertake more R&D investment for providing beneficial knowledge spillover to others. Accordingly, coordinated innovation, as compared to non-coordinated one, can stimulate a higher level of R&D efforts of individual countries and hence the global provision of knowledge.

In particular, I investigate the effect of international R&D coordination on cross-country knowledge diffusion, measured as a percentage change of cumulative knowledge diffusion in the coordinated innovation relative to that in the non-coordinated innovation. As Tab. 5.3 shows, R&D coordination has a positive effect to stimulate foreign knowledge diffusion into individual countries. This is because with the technology externality internalized, individual countries are instructed to enhance country-specific R&D commitment, which brings about more global provisions of public knowledge that is more likely to spill over into individual countries through various diffusion channels.

Figure 5.4: Intertemporal profiles of global R&D spending and the country composition in three innovation scenarios



Note: At each time point, the first column refers to the indigenous innovation scenario, the second column refers to the non-coordinated innovation scenario, and the third column refers to the coordinated innovation scenario

Table 5.3: Effect of international R&D coordination on cross-country knowledge diffusions

	USA	EUW	ROECD	CHN	BRIS	ROW
USA	--	8.2%	7.5%	5.2%	4.9%	4.2%
EUW	12.5%	--	8.5%	4.7%	5.2%	3.8%
ROECD	16.7%	10.2%	--	7.3%	6.8%	5,1%
CHN	18.4%	15.6%	20.1%	--	9.3%	5.4%
BRIS	19.1%	15.3%	14.9%	17.4%	--	4.9%
ROW	8.3%	7.5%	5.8%	7.2%	4.3%	--

Note: To distinguish the destination and source of particular bilateral knowledge diffusion, the row country index denotes destination region that receives foreign knowledge inflows, while the column index represents the source region from which the knowledge diffuse. All values listed in the table are measured as percentage changes of cumulative knowledge diffusions in the coordinated innovation scenario relative to that in the non-coordinated innovation scenario.

However, the magnitude of this positive effect varies significantly across countries. As Tab. 5.3 shows, R&D coordination slightly raises foreign knowledge inflows into the U.S., because the innovation pattern of the world largest R&D investor is largely driven by indigenous R&D, with the complementary effect of foreign knowledge being relatively small. Under multilateral R&D coordination, the EUW and ROECD mostly benefit from foreign knowledge diffused from the U.S., suggesting a close relationship among technologically advanced OECD countries in knowledge sharing and technology cooperation. On the one hand, the OECD countries have intensive linkages of multilateral trade and investment in research-intensive industries, which facilitates the embodied knowledge diffusion through high-tech product transactions. On the other hand, less restriction is imposed on technology transfers among the OECD member countries, which favors the spillovers of disembodied knowledge. Furthermore, technologically advanced countries have existing high levels of knowledge bases and absorptive capacities that favor assimilations of diffused knowledge.

In addition to the North-North technology interaction, Tab. 5.3 also shows the evidence of South-North knowledge diffusion in the process of R&D coordination. The technologically advanced countries (USA, EUW, and ROECD) tend to learn more knowledge created by the BRICS countries, because international technology cooperation also induces the R&D commitments of the emerging countries, which creates differentiated technology varieties that may diffuse into the developed world to complement innovation there.

Turning to China, due to a rapid improvement of its knowledge absorptive capacity, this largest emerging country can harness international R&D cooperation to learn and absorb more knowledge diffused from the OECD advanced countries (USA, EUW, and ROECD). As Tab. 5.3 shows, this is particularly notable for the OECD countries located in the Asia-Pacific region, suggesting that China largely benefits from knowledge diffusions from this region through the established economic linkages, particularly the operation of multinational firms from the USA, Japan, Korea, Singapore, and Hong Kong. As these advanced nations enhance innovative efforts under the multilateral R&D collaboration, the Asia-Pacific economic network may facilitate technological diffusion into the recipient country China.

Tab. 5.3 also shows that other emerging economies like the BRIS are induced to absorb more knowledge diffusions from two global innovation hubs. One is from the traditional technology incumbents located in the OECD, and the other is from China (the world's third largest R&D investor). As knowledge and information sharing become increasingly frequent among the emerging economies, these is also a large potential of the South-South technology cooperation, where the BRIS have an opportunity of learning the knowledge and technology created by China. Meanwhile, similar sophistication levels of production techniques favor mutual adoption and adaptation of technology among the emerging countries.

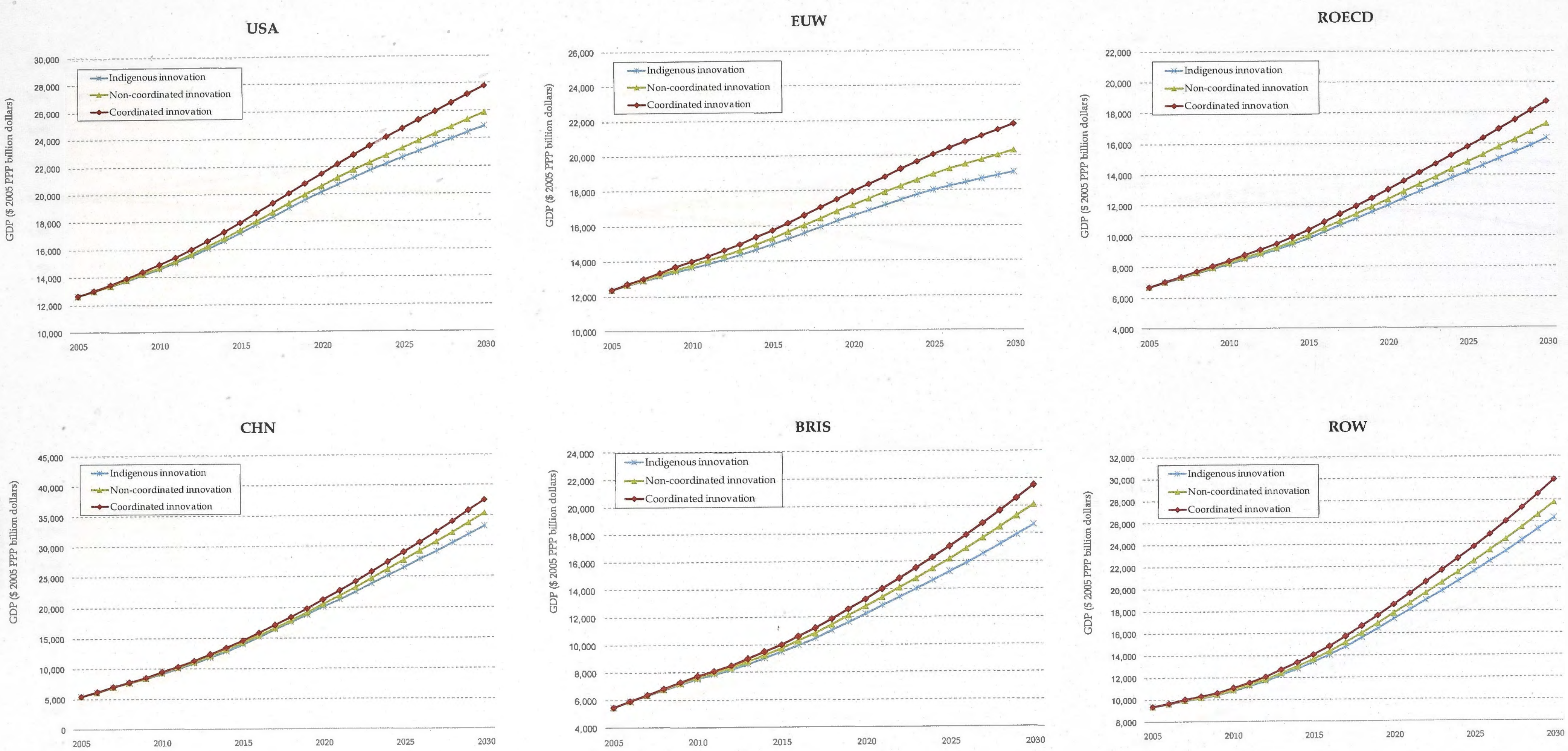
Having examined the effects of R&D coordination on country-specific R&D investment and cross-country knowledge diffusion, I turn to the effects on economic and environmental performance. As shown above, international R&D coordination can accelerate innovation by boosting indigenous R&D investment and cross-country knowledge diffusion. As a result, the enhanced indigenous R&D, with the complement of foreign knowledge inflow, facilitates accumulations of knowledge in each individual country.

The augmented knowledge is then applied in production to induce a reconfiguration of production inputs for productivity gain and output growth (the rate of TC). This is revealed in Fig. 5.5 that displays the GDP growth paths of the six world regions/countries in three innovation scenarios. A common trend is notable: each economy gains the highest growth momentum in coordinated innovation, following by non-coordinated innovation, and finally indigenous innovation. It suggests that international technology cooperation has a positive effect to stimulate economic growth in all participating countries.

Simultaneously, applications of new knowledge in production can lead to knowledge substitution for physical inputs including fossil fuels. Production technique would hence be restructured with a declining use of physical inputs and a rising input of knowledge (the bias of TC). The declining use of fossil energy finally gives rise to a reduction in carbon emissions. This is demonstrated in Fig. 5.6 that shows the carbon emission growth paths of the six world regions/countries in three innovation scenarios. As is to be expected, the coordinated innovation generates an emission path with the lowest growth rate, well below that in both non-coordinated and indigenous innovation. This suggests that international technology cooperation can help restructure economic composition by raising the input of knowledge, which hence lowers carbon emissions in all participating countries.

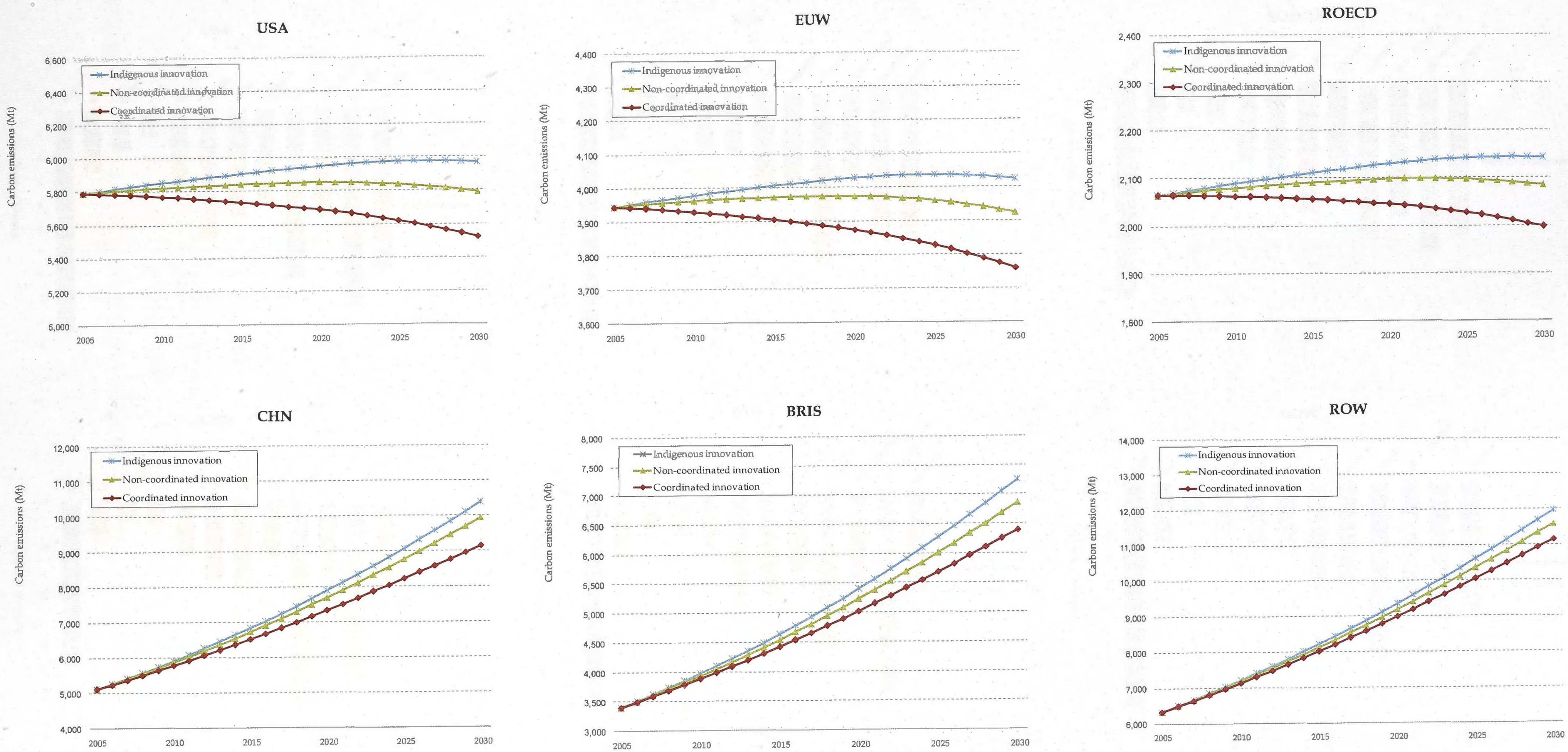
In addition to the economy-wide effect, I further use the multi-sector model structure to capture the sector-level effect of R&D coordination on carbon abatement, which is measured as the percentage reductions of cumulative carbon emissions levels in both uncoordinated and coordinated innovation relative to that in indigenous innovation. As Fig. 5.7 shows, on top of non-coordinated innovation, R&D coordination generates sizable additional increases in carbon abatement in twelve production sectors. In particular, the sectors of electric utility, manufacturing, and transport have higher carbon saving potential, because production technologies in these sectors have an intensive use of fossil energy inputs, and thus have a large room of applying new knowledge (induced by R&D coordination) to substitute for fossil energy. Meanwhile, USA, China, and other emerging countries achieve comparatively higher carbon-saving benefits from technology cooperation with the economies that are relatively "green" like Germany in EUW and Japan in ROECD.

Figure 5.5: Economic growth paths (measured as GDP) of the six world regions in three innovation scenarios



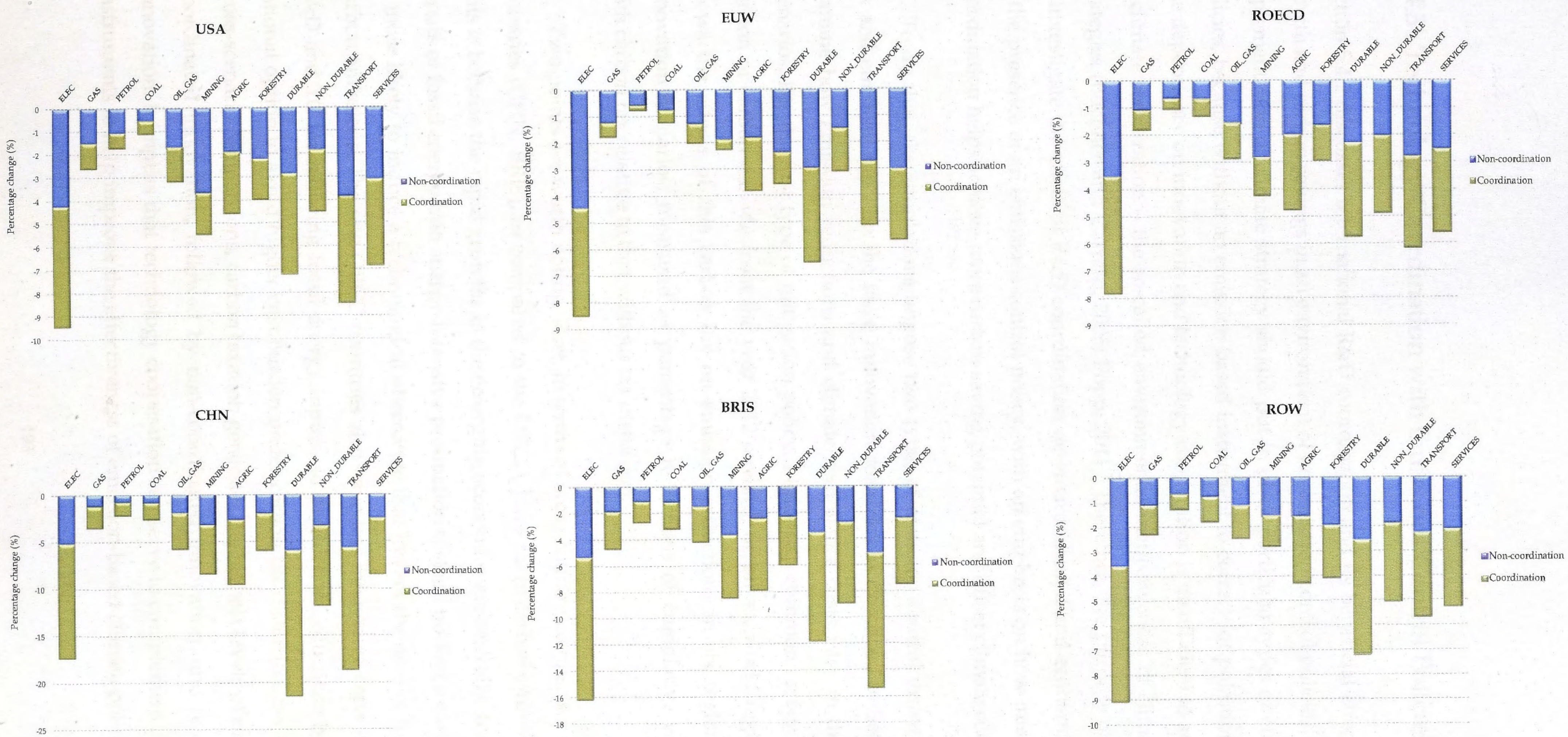
Note: Each economy gains the highest growth momentum in coordinated innovation, following by non-coordinated innovation, and finally indigenous innovation

Figure 5.6: Carbon emissions growth paths of the six world regions in three innovation scenarios



Note: In each world region, the coordinated innovation scenario generates an emission path with the lowest growth rate, which is well below that in both non-coordinated and indigenous innovation

Figure 5.7: Effect of international R&D coordination on sector-level carbon abatements in the six world regions



Note: The effect is measured as percentage reductions of sector-specific cumulative emissions driven by international R&D coordination relative to the emission levels without R&D coordination

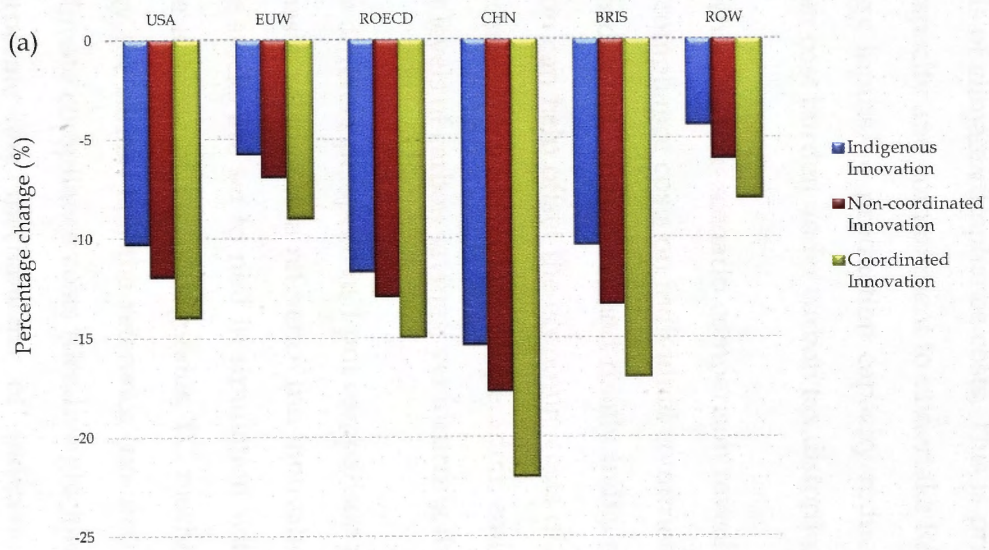
5.4.3 Technology Coordination with Emissions Control Policies

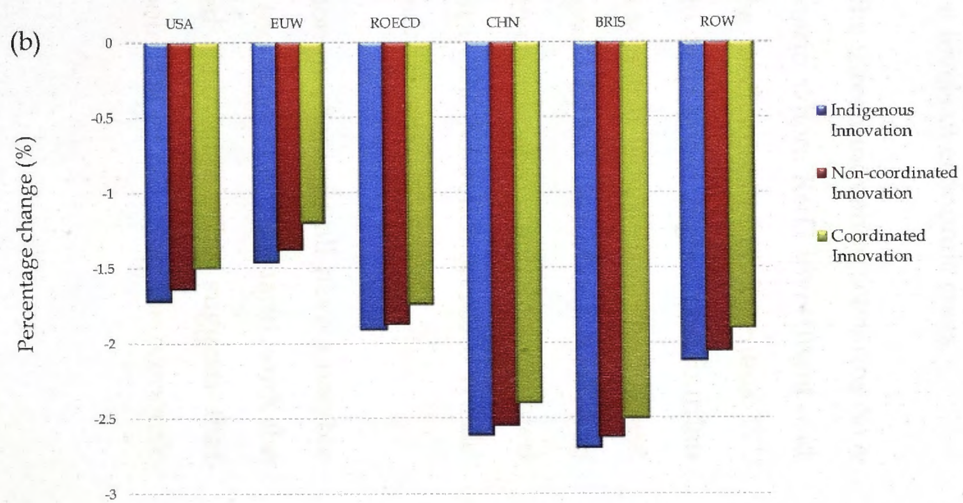
Section 5.4.2 discusses international R&D coordination and its beneficial effect on economic growth and carbon savings in an environment of no-emission control policies. However, real implementation of climate strategy should put in place particular types of emission control policies, because without an emission-based instrument to correct for pollution externality, a sole dependence on innovation and technology cooperation is insufficient to achieve the goal of climate stabilization - the so-called environmental ineffectiveness of climate technology strategies (Buchner and Carraro, 2005; Popp, 2011). Therefore, the purpose of this section is to investigate the effect of R&D coordination on environmental and economic performance in the presence of an emissions control policy, with an emphasis on how international R&D coordination helps achieve more carbon saving potential and offset climate compliance cost.

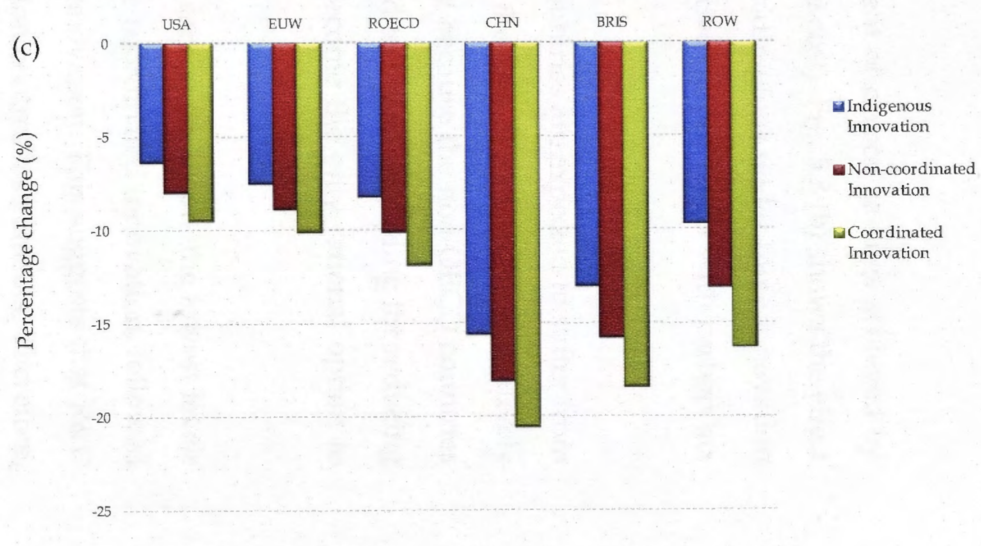
To do that, the simulations impose two types of emission control instruments - carbon tax and emission cap - on the three innovation scenarios as described in Section 5.4.1, and examine how emission reductions and climate compliance costs vary in these innovation scenarios. For the first type of mitigation policy, I impose a common carbon tax, $20 dollar per ton of carbon dioxide from the year 2012 onward, on all six world regions. Fig. 5.8(a) shows the effects of this carbon tax on emission reductions in six regions under three innovation scenarios, measured as percentage reductions of cumulative emissions levels with carbon tax relative to that without tax distortion.

Two points are worth noting. First, in terms of cross-country comparisons, the emerging countries (CHN, BRIS), as compared to the OECD, have more carbon emissions reductions. This is because the rapid growths in the emerging economies are basically driven by massive inputs of fossil energy into energy-intensive production system, putting a carbon price signal is more likely to induce a technological alternative that lowers the uses of fossil energy and carbon emissions. The non-OECD countries also have less innovative capacity to undertake R&D and TC for reducing fossil energy inputs, so production reductions become the only rational option to avoid higher cost burden under carbon tax distortion. Second, in terms of cross-scenario comparisons, carbon taxation generates the highest levels of carbon savings in coordinated innovation, followed by non-coordinated innovation, and finally indigenous innovation. It implies that technology cooperation can serve to complement emission control instruments to help improve the effectiveness of emission-based climate policies.

Figure 5.8: (a) Effect of carbon tax to lower cumulative emission levels in six countries under three innovation scenarios; (b) Effect of carbon tax to incur cumulative production output losses in six countries under three innovation scenarios; (c) Effect of introducing three innovation mechanisms to partially offset climate compliance costs (incurred by carbon tax) in reference (no-innovation) scenario.







Meanwhile, it is notable that the environmental benefit of carbon savings achieved by carbon taxation is at an economic cost (climate compliance cost). Fig. 5.8 (b) shows the effect of carbon taxation on production output losses in six world regions under three innovation scenarios, measured as percentage reductions of cumulative output levels with carbon tax relative to that without tax distortion.

A cross-country comparison shows that non-OECD countries are expected to suffer from more output losses under the carbon tax burden, while the OECD nations have relatively lower levels of climate compliance costs. This is primarily because the non-OECD countries have less capacity and commitment to undertake R&D and technical upgrading for reducing fossil energy inputs, so production capacity reduction become the only rational option to avoid higher cost burden under carbon tax distortion.

Meanwhile, a cross-scenario comparison reveals that carbon tax incurs the lowest levels of climate compliance costs on individual countries in the coordinated innovation, followed by non-coordinated innovation, and finally indigenous innovation. This suggests that R&D coordination can help offset the economic costs of emission control instruments. Therefore, through cross-country technology cooperation, emission-based climate policies can generate the highest levels of carbon savings, yet incurring the lowest levels of economic costs.

From a different perspective, I put comparison across the three innovation scenarios on a common basis: relative to a reference (no-innovation) scenario where R&D investment and knowledge stocks are set to null in simulation without the mechanism of endogenous TC. Due to the absence of the endogenous TC mechanism to help avoid higher cost burden incurred by the carbon tax, the reference (no-innovation) scenario would have the highest levels of climate compliance costs (deadweight losses incurred by tax distortion). Next, I in turn incorporate the mechanisms of indigenous, non-coordinated, and coordinated innovation, and examine how the climate compliance cost in the reference scenario would change in response to introducing these three innovation mechanisms.

As Fig. 5.8(c) reveals, incorporating the three innovation mechanisms all have a notable effect to reduce climate compliance costs in the reference (no-innovation) scenario, with the highest levels of reductions occurring in the coordinated innovation. This suggests that international technology cooperation can maximize the potential of reducing the economic costs incurred by emission control policies. In particular, the emerging economies like CHN and BRIS can harness international technology cooperation to reduce more domestic climate compliance costs. This suggests that R&D cooperation should be introduced to synergize an emission-based agreement for offsetting climate compliance costs. By doing that, the major carbon emitters could have incentives to participate in international climate agreement.

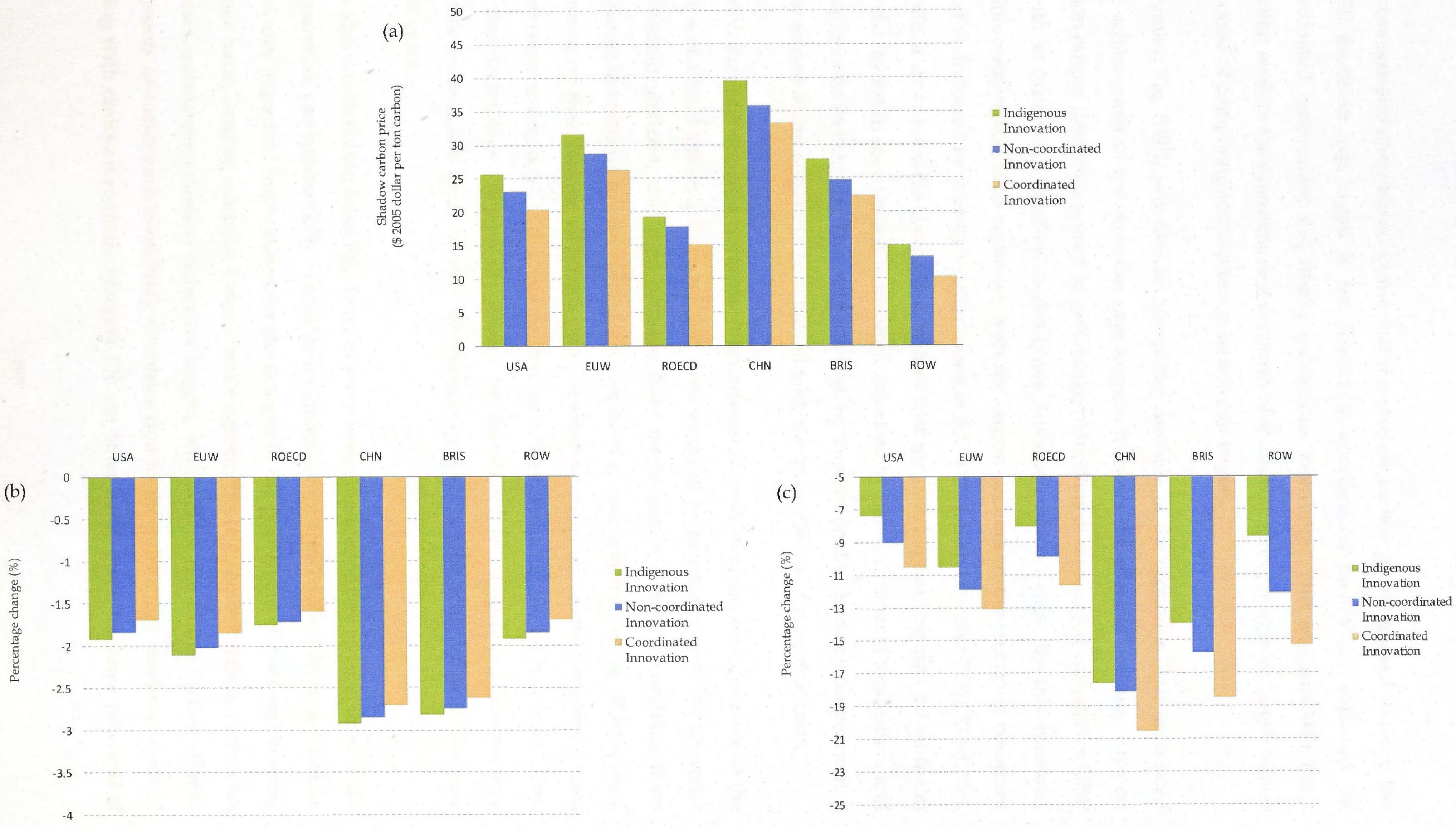
Consider the second type of emission control policy – emission cap. I set an emission cap that reduces the year 2030 (end year of simulation) carbon emission levels by 20% relative to the year 2005 (base year) levels in each of the six world regions.[21] To impose this particular type of emission caps, I assume that a shadow carbon price is put on each of the six world regions in year 2012 (the expiring year of the Kyoto Protocol compliance period) and then rises at 5% growth rate by 2030 (reflecting a rising marginal abatement cost), so that all individual countries can domestically achieve their year 2030 emission cap targets.

The economic consequences of this emission cap vary significantly across countries and innovation scenarios. Fig. 5.9(a) provides a measure of the economic costs of complying with the emission caps (marginal abatement cost when emission binding occurs). It represents the shadow carbon price imposed on each economy in the year 2012 so that the year 2030 emission cap target can be achieved Measured in this term, climate compliance cost is the highest in China, which has its 2012 shadow carbon price about $40 per ton. Next in order of climate mitigation burden is E.U. and BRIS, with a 2012 carbon price of $30. Somewhat lower are the U.S. and ROECD, both of which have 2012 carbon prices about $20 per ton.

The reason for higher climate compliance costs in China is that, as the world's largest carbon emitter, this country has taken strong efforts to cut its carbon emissions, making its year 2005 emission levels already at a relatively lower level. Thus, cutting such a lower base year emission level by 20% by 2030 will become a relatively stringent target, which translates into higher compliance costs suffered by China for achieving this emissions reduction target.

[21] Note that, as compared to the carbon tax that is uniformly imposed on individual countries, the setting of emission caps is in nature not uniform. That is, although the settings of 20% relative emissions reductions (year 2030 relative to year 2005) are the same, the corresponding absolute levels of reductions are different across countries due to different base year emission levels (McKibbin et al., 2011).

Figure 5.9: (a) Shadow carbon prices generated by emission caps in the six world regions under three innovation scenarios;
(b) Effect of emission caps on cumulative production output losses in the six world regionsunder three innovation scenarios;
(c) Effect of three innovation mechanisms to offset economic costs (incurred by emission cap) in reference (no-innovation) scenario



A cross-scenario comparison shows that the shadow carbon price imposed to reach the year 2030 emission cap target is the lowest in coordinated innovation, followed by non-coordinated innovation, and finally indigenous innovation. This suggests that R&D coordination enables the economic cost (in terms of shadow carbon price) to be largely offset in the process of complying with certain emission cap targets.

Moreover, Fig. 5.9(b) provides an alternative measure of the economic costs associated with the achievement of the emission caps targets. It shows the effect of emission caps on production output losses, measured as percentage reductions of discounted cumulative GDP levels with emission cap relative to the levels without emission caps. By this measure, production outputs fall in all countries with the largest declines in the emerging countries (-2.5%~ -3%), followed by slightly smaller losses in E.U. (-2%), then U.S. and ROECD (-1.5%). Meanwhile, a cross-scenario comparison shows that the cost burden imposed by emission caps are the lowest in coordinated innovation, followed by non-coordinated innovation, and finally indigenous innovation. This suggests that, by international technology cooperation, a particular emission cap target can be achieved with the lowest levels of economic costs.

Finally, the cross-scenario comparison is undertaken on a common basis (relative to the reference scenario), I simulate the economic costs incurred by emission cap in the reference (no-innovation) scenario, and then compare how the reference climate compliance costs would change in response to introducing three innovation mechanisms. As Fig. 5.9(c) shows, three innovation mechanisms all have a positive effect to mitigate climate compliance costs in the reference scenario, with the coordinated innovation reducing the highest levels. This implies that technology cooperation should be introduced to complement international agreements on emission caps, so that the emission targets can be achieved with the least economic costs.

It is also worth noting from Fig. 5.9(c) that the emerging economies, as compared to the OECD countries, can substantially reduce their climate compliance cost in R&D coordination. This provides important implications for the designs of the post-Kyoto climate architecture. On the one hand, existing emission-based climate agreements (e.g., emission caps, carbon tax) emphasizes mandatory emission reduction targets, which gives rise to insufficient climate commitments of major carbon-emitting countries due to the substantial economic costs of complying with emission reduction targets. On the other hand, given the large potential of international technology cooperation in facilitating innovation and technology progress, an international climate architecture combining both emission-based and technology-oriented agreements may create a synergic effect to lower the costs of climate compliance. By doing that, climate commitment made by individual countries can be strengthened, which further improve the environmental effectiveness of their collective climate mitigation efforts.

5.5 Conclusions

Beyond the rapid economic growth, the stories in the emerging countries like the BRICS countries are increasingly about technological innovation, which has remarkably changed the former Triad-region (USA, EU, and Japan) innovation pattern into a new landscape of global innovation with multiple hubs of R&D. As the emergence of multiple hubs of innovation is anticipated to facilitate cross-country knowledge sharing and multilateral technology cooperation, climate strategies should introduce particular international technology-oriented agreements to complement existing emission-based one in formulating the post-2012 climate architecture.

This chapter provides a new attempt to investigate the mechanism of international technology cooperation and its effect on global climate mitigation. I firstly present a simple framework that analyzes the mechanism of international R&D coordination and its effect on reducing climate mitigation costs. This mechanism is then quantitatively investigated in a multi-region numerical model that explicitly represents the positive technology externality resulting from cross-country knowledge diffusions.

Simulation results show that: (1) By internalizing the positive externality of reciprocal knowledge diffusions, multilateral R&D coordination can induce more R&D efforts made by individual countries and hence the global provisions of knowledge that favor innovation across countries; (2) Innovative efforts enhanced by international R&D coordination facilitate new knowledge creation and application, which can stimulate the potential of economic growth and carbon savings in all participating countries (3) Multilateral R&D coordination (technology-oriented agreements) can synergize with traditional emission-based climate agreements to help lower the economic costs of emission control policies, hence improving the participation incentives of major carbon-emitting countries and the environmental effectiveness of their collective mitigation efforts in global climate governance.

Appendix to Chapter 5

5.A Derivation of the Relationship between MAC and Knowledge Input

The producer problem can be formulated as follows:

$$\min \quad P_D \cdot E_D + P_C \cdot E_C$$

$$\text{s.t.} \quad \left[\left(E_D^{\sigma_E} + E_C^{\sigma_E}\right)^{\frac{\sigma_Y}{\sigma_E}} + H^{\sigma_Y}\right]^{\frac{1}{\sigma_Y}} = Y; \qquad E_C > 0; \qquad \bar{\kappa} \geq E_D > 0$$

where the corresponding Lagrangian can be expressed as follows:

$$L = -(P_D \cdot E_D + P_C \cdot E_C) + \lambda_Y \cdot \left[\left(E_D^{\sigma_E} + E_C^{\sigma_E}\right)^{\frac{\sigma_Y}{\sigma_E}} + H^{\sigma_Y} - Y^{\sigma_Y}\right] + \lambda_D \cdot (\bar{\kappa} - E_D) + \lambda_C \cdot E_C$$

The first order condition (F.O.C) with respect to two endogenous control variables yields:

$$\begin{cases} \dfrac{\partial L}{\partial E_D} = -P_D + \lambda_Y \cdot \dfrac{\sigma_Y}{\sigma_E} \cdot \left(E_D^{\sigma_E} + E_C^{\sigma_E}\right)^{\frac{\sigma_Y}{\sigma_E}-1} \cdot \sigma_E \cdot E_D^{\sigma_E - 1} - \lambda_D = 0 \\ \dfrac{\partial L}{\partial E_C} = -P_C + \lambda_Y \cdot \dfrac{\sigma_Y}{\sigma_E} \cdot \left(E_D^{\sigma_E} + E_C^{\sigma_E}\right)^{\frac{\sigma_Y}{\sigma_E}-1} \cdot \sigma_E \cdot E_C^{\sigma_E - 1} + \lambda_C = 0 \end{cases}$$

where the complementary slackness condition with respect to three costate variables (shadow price of the corresponding constraint) are as:

$$\begin{cases} \dfrac{\partial L}{\partial \lambda_Y} = \left(E_D^{\sigma_E} + E_C^{\sigma_E}\right)^{\frac{\sigma_Y}{\sigma_E}} + H^{\sigma_Y} - Y^{\sigma_Y} \geq 0; \quad \lambda_Y \geq 0; \quad \dfrac{\partial L}{\partial \lambda_Y} \cdot \lambda_Y = 0 \\ \dfrac{\partial L}{\partial \lambda_D} = \bar{E} - E_D \geq 0; \quad \lambda_D \geq 0; \quad \dfrac{\partial L}{\partial \lambda_D} \cdot \lambda_D = 0 \\ \dfrac{\partial L}{\partial \lambda_C} = E_C \geq 0; \quad \lambda_C \geq 0; \quad \dfrac{\partial L}{\partial \lambda_C} \cdot \lambda_C = 0 \end{cases}$$

Given that emission abatement occurs in the presence of carbon emission caps, then abatement boundary condition should be satisfied with $\bar{\kappa} - E_D = 0$, $E_D > 0$, and the K-T condition becomes:

$$
\begin{cases}
\dfrac{\partial L}{\partial E_D} = -P_D + \lambda_Y \cdot \sigma_Y \cdot \left(E_D{}^{\sigma_E} + E_C{}^{\sigma_E}\right)^{\frac{\sigma_Y}{\sigma_E}-1} \cdot E_D{}^{\sigma_E - 1} - \lambda_D = 0 & (5.A.1) \\
\dfrac{\partial L}{\partial E_C} = -P_C + \lambda_Y \cdot \sigma_Y \cdot \left(E_D{}^{\sigma_E} + E_C{}^{\sigma_E}\right)^{\frac{\sigma_Y}{\sigma_E}-1} \cdot E_C{}^{\sigma_E - 1} + \lambda_C = 0 & (5.A.2) \\
\dfrac{\partial L}{\partial \lambda_Y} = \left(E_D{}^{\sigma_E} + E_C{}^{\sigma_E}\right)^{\frac{\sigma_Y}{\sigma_E}} + H^{\sigma_Y} - Y^{\sigma_Y} = 0; \quad \lambda_Y > 0 & (5.A.3) \\
\dfrac{\partial L}{\partial \lambda_D} = \overline{\kappa} - E_D = 0; \quad \lambda_D > 0 & (5.A.4) \\
\dfrac{\partial L}{\partial \lambda_C} = E_C > 0; \quad \lambda_C = 0 & (5.A.5)
\end{cases}
$$

From Eq. (5.A.4), we have $E_D = \overline{\kappa}$, substitute into Eq. (5.A.3), yields

$$
E_C = \left[\left(Y^{\sigma_Y} - H^{\sigma_Y}\right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E}\right]^{\frac{1}{\sigma_E}} \tag{5.A.6}
$$

Substitute Eq. (5.A.6), $E_D = \overline{\kappa}$, $\lambda_C = 0$ into Eq. (5.A.2), yields

$$
-P_C + \lambda_Y \cdot \sigma_Y \cdot \left(\overline{\kappa}^{\sigma_E} + \left(Y^{\sigma_Y} - H^{\sigma_Y}\right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E}\right)^{\frac{\sigma_Y}{\sigma_E}-1} \cdot \left[\left(Y^{\sigma_Y} - H^{\sigma_Y}\right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E}\right]^{\frac{\sigma_E - 1}{\sigma_E}} = 0 \tag{5.A.7}
$$

$$
\Rightarrow \lambda_Y = P_C \cdot \sigma_Y{}^{-1} \cdot \left(Y^{\sigma_Y} - H^{\sigma_Y}\right)^{\frac{\sigma_E - \sigma_Y}{\sigma_Y}} \cdot \left[\left(Y^{\sigma_Y} - H^{\sigma_Y}\right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E}\right]^{\frac{1-\sigma_E}{\sigma_E}}
$$

Substitute Eqs. (5.A.6)-(5.A.7), $E_D = \overline{\kappa}$ into Eq. (5.A.1), yields

$$
\begin{aligned}
\lambda_D &= -P_D + \lambda_Y \cdot \sigma_Y \cdot \left(\overline{\kappa}^{\sigma_E} + \left(Y^{\sigma_Y} - H^{\sigma_Y}\right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E}\right)^{\frac{\sigma_Y - \sigma_E}{\sigma_E}} \cdot \overline{\kappa}^{\sigma_E - 1} \\
&= -P_D + \lambda_Y \cdot \sigma_Y \cdot \left(Y^{\sigma_Y} - H^{\sigma_Y}\right)^{\frac{\sigma_Y - \sigma_E}{\sigma_Y}} \cdot \overline{\kappa}^{\sigma_E - 1} \\
&= -P_D + P_C \cdot \left[\left(Y^{\sigma_Y} - H^{\sigma_Y}\right)^{\frac{\sigma_E}{\sigma_Y}} - \overline{\kappa}^{\sigma_E}\right]^{\frac{1-\sigma_E}{\sigma_E}} \cdot \overline{\kappa}^{\sigma_E - 1}
\end{aligned}
$$

■

5.B Country Composition of Regions

Region Number	*Region Name*	*Region Description*
1	USA	United States of America
2	EUW	Western Europe
3	ROECD	Rest of the OECD
4	CHN	China
5	BRIS	Brazil, Russia, India, South Africa
6	ROW	Rest of the World

Western Europe:

Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom

Rest of the OECD:

Canada, Australia, New Zealand, Japan, Korea, Singapore, Hong Kong, Taiwan

Rest of the World:

All countries not included in other region groups

Model sectoral classification and mapping by reference to the GTAP and OECE ANBERD

Sector number/name in our mode	GTAP sector numbers	OECD ANBERD sector number
1. Electric utilities	43	40
2. Gas utilities	44	41
3. Petroleum refining	32	23
4. Coal mining	15	10
5. Crude oil & gas extraction	16-17	11
6. Mineral mining	18	12-14
7. Agriculture	01-12, 14	01, 03-05
8. Forestry & wood products	13, 30	02, 20
9. Durable manufacturing	34-42	26-37
10. Nondurable manufacturing	19-29, 31, 33	15-19, 21-22, 24-25
11. Transportation	48-50	60-64
12. Services	45-47, 51-57	45, 50-59, 70-99

5.C GEMPACK TABLO Model Codes

The Chapter 5 model focuses on representing multilateral R&D spillovers among the six world regions (e.g., USA, EUW, ROECD, CHN, BRIS, ROW). That is, innovation in each region depends on both indigenous R&D and international TD, and the model explicitly describes international knowledge diffusion into each world region through three diffusion channels. Hence, in a decentralized non-cooperative R&D equilibrium, the modeling structure for each world region is similar to the China part in the Chapter 4 model (as outlined in Chapter 4 Appendix 4.C). As the other alternative equilibrium, the centralized cooperative innovation case can be characterized by the following TABLO codes.

```
!=================================================================

GEMPACK TABLO code for implementing the centralized coopearative innovation
equilibrium as outlined in the thesis Chapter 5
==================================================================!

!==============================================================
R&D spending level in a fully cooperative innovation equilibrium
==============================================================!

SET regions  # 6 world regions in cross-region technology interaction #
(USA, EUW, ROECD, CHN, BRIS, ROW);
SET origin # origin regions providing knowledge outflows # = regions;
SET destination # destination regions receiving knowledge inflows # = regions;


Variable
prrr(n,t)       # price of raw R&D good #;
delTRTC(n,t)    # rate of R&D tax credit #;
wcbr(i,n,t)     # within-country benefit from indigenous R&D investment #;
ccbr(i,n,t)     # cross-country benefit from knowledge spillover #;
lamr(n,i,t)     # shadow price of knowledge capital #;
rnv(n,i,t)      # R&D investment #;
hcp(n,i,t)      # knowledge capital stock #;
rnv_r(i,t)      # global R&D investment as a sum of invididual country R&D #;
rtac(r,i,t)     # knolwedge absorptive capacity for assimilating R&D spillover #;
enff(n,r,i,t)   # intermediate input import flows from origin country n to
                  destination country r #;
invff(n,r,i,t) # FDI investment inflows from origin country n to destination country
r #;
ouy(n,i,t)      # output of commodity i produced in origin country n #;
delBART         # foreign barrier of international trade #;
delBARF         # foreign barrier of international investment #;
delBARD         # foreign restriction of knowledge spillover #;


Coefficient
(all,n,origin) (all,i,sectors) (all,t,alltime)          S_H1(n,i,t);
(all,n,origin) (all,i,sectors) (all,t,alltime)          S_H2(n,i,t);
(all,n,origin) (all,i,sectors) (all,t,alltime)          S_H3(n,i,t);
(all,n,origin) (all,i,sectors) (all,t,alltime)          S_H4(n,i,t);
(all,n,origin) (all,i,sectors) (all,t,alltime)          S_H5(n,i,t);
Formula
(all,n,origin) (all,i,sectors) (all,t,alltime)
S_H1(n,i,t) = LLAMR(n,i,t)* [ALPHA*AH*(LRNV(n,i,t)^(ALPHA-1))*(LHCP(n,i,t)^BETA)
            + BARD - 2*LRNV(n,i,t)/LRNV_R(i,t)]
            / {LLAMR(n,i,t)* [ALPHA*AH*(LRNV(n,i,t)^(ALPHA-1))*(LHCP(n,i,t)^BETA)
            + BARD - 2*LRNV(n,i,t)/LRNV_R(i,t)]
```

```
            + sum{r,destination,LLAMR(r,i,t)*LRTAC(r,i,t)
            * [BART*V1(n,r,i,t)/V1_Y(n,i,t) + BARF * LRNV (n,r,i,t)/V1_Y(n,i,t) +
              BARD] }};

(all,n,origin)(all, i, sectors) (all, t, alltime)
S_H2(n,i,t) = ALPHA*AH*(LRNV(n,i,t)^(ALPHA-1))*(LHCP(n,i,t)^BETA)
            / [ALPHA*AH*(LRNV(n,i,t)^(ALPHA-1))*(LHCP(n,i,t)^BETA)
            + BARD - 2*LRNV(n,i,t)/LRNV_R(i,t)];

(all,n,origin)(all,r,destination)(all, i, sectors) (all, t, alltime)
S_H3(n,r,i,t) = LLAMR(r,i,t)*LRTAC(r,i,t)*[BART*V1(n,r,i,t)/V1_Y(n,i,t)
              + BARF*LRNV (n,r,i,t)/V1_Y(n,i,t) + BARD]
              / sum{r, destination, LLAMR(r,i,t)*LRTAC(r,i,t)
              * [BART*V1(n,r,i,t)/V1_Y(n,i,t) + BARF*LRNV (n,r,i,t)/V1_Y(n,i,t) +
                BARD]};

(all,n,origin)(all,r,destination)(all, i, sectors) (all, t, alltime)
S_H4(n,r,i,t) = BART*V1(n,r,i,t)/V1_Y(n,i,t)
              / [BART*V1(n,r,i,t)/V1_Y(n,i,t) + BARF*LRNV (n,r,i,t)/V1_Y(n,i,t) +
                BARD];

(all,n,origin)(all,r,destination)(all, i, sectors) (all, t, alltime)
S_H5(n,r,i,t) = BARF*LRNV (n,r,i,t)/V1_Y(n,i,t)
              / [BART*V1(n,r,i,t)/V1_Y(n,i,t) + BARF*LRNV (n,r,i,t)/V1_Y(n,i,t) +
                BARD];

Equation
E_prrr # R&D spending in the presence of  within-country and cross-country benefit#
(all,n,origin) (all,i,sectors) (all,t,alltime)
prrr(n,t) - 100 /(1-TRTC(n,t)) * delTRTC(n,t)
= S_H1(n,i,t)*wcbr(n,i,t) + (1-S_H1(n,i,t))*ccbr(n,i,t);


E_wcbr # within-country benefit from indigenous R&D spending #
(all,n,origin) (all,i,sectors) (all,t,alltime)
wcbr(n,i,t) = lamr(n,i,t)
            + S_H2(n,i,t) * [(ALPHA-1)*rnv(n,i,t) + BETA*hcp(n,i,t)]
            + (1-S_H2(n,i,t))
            * [2*LRNV(n,i,t)/(2*LRNV(n,i,t)-BARD*LRNV_R(i,t))]
            * [rnv(n,i,t)-rnv_r(i,t)];


E_wcbr # cross-country spillover benefit from indigenous R&D spending #
(all,n,origin) (all,i,sectors) (all,t,alltime)
ccbr(n,i,t) = sum {r, destination, S_H3(n,r,i,t)* [lamr(r,i,t) + rtac(r,i,t)
            + S_H4(n,r,i,t)*(100/BARF*delBART + enff(n,r,i,t) - ouy(n,i,t))
            + S_H5(n,r,i,t)*(100/BARF*delBARF + invff(n,r,i,t) - ouy(n,i,t))
            + (1-S_H4(n,r,i,t)-S_H5(n,r,i,t))*(100/BARD*delBARD)]};
```

Chapter 6

Conclusions

6.1 Major Findings

The overarching focus of climate policies to avert the threat of dangerous global warming is mitigation, i.e., carbon emissions reduction. Carbon abatement has profound implications for the use of fossil energy. On the one hand, fossil fuels are indispensable energy inputs into virtually every industry in an economy. On the other hand, there are currently no effective substitutes for fossil fuels as energy carriers. For these reasons climate economic analysis generally predicts that carbon emission controls will precipitate large increases in fossil energy prices, and result in significant reductions in economic production. Of all the factors that influence the prediction of the likely costs of carbon abatement, technology plays the most important role. Designing an economically optimal strategy of carbon abatement thus requires a deep understanding of the mechanism of technological innovation and its interaction with climate mitigation policies.

Chapter 2 presents a conceptual framework that unveils the endogenous mechanism through which TC is induced by climate policies. The central finding without extending to the microeconomic foundation of innovation, profit-seeking private firms, to avoid the higher cost burden imposed by climate regulation, will undertake purposeful innovative activities as a response to increases in fossil energy prices. This underlying mechanism can be further represented as three concomitant endogenous processes: 1) R&D inducement: emissions control policies raise the cost of using fossil energy, with the signal of a higher energy price inducing private firms to undertake purposeful innovative activities in the form of R&D investment; 2) Knowledge creation: the stock of productive knowledge base is augmented by the purposeful R&D investment; 3) Production TC: the accumulated knowledge capital is applied in a production process for TC, with an outcome of shifting out production possibility

Chapter 6

Conclusions

6.1 Major Findings

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Chapter 2 presents a conceptual framework that unveils the endogenous mechanism through which TC is induced by climate policies. The central finding is that, according to the microeconomic foundation of innovation, profit-seeking private firms, to avoid the higher cost burden imposed by climate regulation, will undertake purposeful innovative activities as a response to increases in fossil energy prices. This underlying mechanism can be further represented as three consecutive endogenous processes: 1) R&D inducement: emissions control policies raise the cost of using fossil energy, with the signal of a higher energy price inducing private firms to undertake purposeful innovative activities in the form of R&D investment; 2) Knowledge creation: the stock of productive knowledge asset is augmented by the purposeful R&D investment. 3) Production TC: the accumulated knowledge capital is applied in a production process for TC, with an outcome of shifting out *production possibility* *frontier* and substituting knowledge for costly energy inputs.

In the process of R&D inducement, the principal finding is that whether the purposeful R&D investment of private firms can be induced by raising fossil energy price (through government regulation on emissions control) depends on the interaction of four effects in equilibrium: 1) Input cost effect; 2) Output price effect; 3) Market demand effect; and 4) Innovation uncertainty effect. The second and fourth effects are positive on inducing R&D investment, while the first and third effects being negative.

In the process of knowledge creation, it is found that there are two different views about the characteristics of knowledge: the excludability of innovation *vis-a-vis* the non-rivalry of idea. With a view of science, it is appropriate to regard the non-rivalry and non-excludability as the general attributes of knowledge. Meanwhile, in an economic sense, it is plausible to think of the idea as an economically useful knowledge that is largely excludable to competitors within an intellectual property protection system in the real - world economy. To reconcile both alternative views, I describe an innovation process that features both sector-specific R&D and external knowledge spillover as the dual sources of knowledge creation. This kind of treatment is particularly relevant to modeling innovation within a multi-sector economic framework, where intersectoral R&D spillovers are most likely to occur through multi-sector economic transactions.

In the process of production TC, the main finding is that, by applying new knowledge (created in the innovation process) in a production process, the *production possibility frontier* would shift out, with an increase in the Hicks-neutral total factor productivity (the rate of production TC). Meanwhile, there is a decline in the cost share of each physical input and a rise of knowledge input (the bias of production TC). The effect of knowledge application on production TC can thus be characterized as knowledge substitution for physical inputs with a saving of them (including fossil energy).

Chapter 3 develops an intertemporal optimization CGE model of the Chinese economy to analyze the effect of technological innovation on the timing and cost of carbon abatement. I find that an intertemporal framework, as compared to a myopic recursive-dynamic one, is better suitable for incorporating the mechanism of endogenous TC into a traditional CGE model, because representing R&D-induced TC in an intertemporal model is more consistent with the microeconomic foundation of innovation, with R&D investment and knowledge use being modeled as the endogenous economic behaviors of profit-seeking firms.

It is also found that in a disaggregated framework like a multi-sector CGE model, it is necessary to explicitly consider and represent the positive technology externality resulting from intersectoral knowledge spillovers. That is, due to the imperfect appropriability of knowledge, physical goods produced by individual sector could partially embody intangible knowledge created by sector-specific R&D investment. Other sectors, in the multi-sector economic transaction, can benefit from external knowledge spillover through the sectoral linkages along the supply chains – the so-called intersectoral knowledge spillovers.

The procedure of model calibration shows that a stylized input-output (IO) dataset is not well suited to calibrate a CGE model featuring the R&D-induced TC, because it does not separately record economic flows associated with R&D investment and knowledge inputs. In a more theoretically consistent way, the technique of knowledge accounting, in line with the embodied technology hypothesis, can be used to construct a modified IO dataset with an explicit representation of R&D investments and knowledge inputs, based on which the CGE model with R&D-induced TC is calibrated.

The results of numerical simulation indicate that 1) Technological progress induced by R&D commitment has a notable effect to curb China's carbon emissions levels, with the sectors of manufacturing, electricity, and transport having the highest carbon abatement potential from innovation; 2) Indigenous R&D investments are important as the technology strategies to address climate change mitigation, but the sole dependence on R&D is far from sufficient to achieve the pledged climate target, because China's innovation pattern is basically "normal" with a focus on productivity improvement rather than carbon saving; 3) Innovation policies (public R&D subsidy and stringent IPR) can strengthen R&D investment and further reduce carbon emissions, but this complementary effect is still minor and insufficient to meet the stipulated climate target. This is primarily because continued growth in public R&D may suffer from diminishing return in innovation, and stringent IPR system only serves to protect the *ex post* excludability of innovation, which may be ancillary to the *ex ante* incentive of R&D investment as an inventive response to price signal; 4) Emission-based climate regulation through carbon taxation are necessary to fulfill the emission reduction target, but achieving this carbon-saving benefit is at the cost of sizable production output losses; 5) Stringent climate regulation induces the incentive of private firms to innovate and technical upgrading, which can partially mitigate the deadweight losses incurred by carbon tax distortion.

Chapter 4 extends the single-country model into a multi-region global framework, into which the mechanism of international technology diffusion is incorporated. The implications are two-fold. First, due to a backward position in the global technology ladder, innovations in developing nations can benefit from knowledge diffusion from technologically advanced countries. International knowledge diffusion thus plays an important role to complement indigenous R&D in fostering innovation and TC in developing countries. Second, domestic economy can acquire external foreign knowledge through two mechanisms: 1) Embodied knowledge diffusion through indirectly employing knowledge-embodied intermediate and capital goods; 2) Disembodied knowledge diffusion through directly learning disembodied knowledge spillover.

Embodied knowledge diffusion (passive knowledge diffusion) occurs when domestic firms indirectly benefit from external innovation by using knowledge-embodied foreign intermediate commodity (via import) or capital goods (via FDI). In parallel, disembodied knowledge diffusion (active knowledge diffusion) involves direct learning and absorption of the disembodied forms of technologies (e.g., formulas, blueprints, patents), not necessarily linking to the economic transactions of tangible physical goods in international trade and investment. Therefore, international technology diffusion occurs via three channels: trade, FDI, and disembodied knowledge spillover. Meanwhile, while knowledge can diffuse from abroad through three diffusion channels, the efficiencies of assimilating the diffused knowledge of the recipient developing countries are localized due to their differentiated indigenous capacities of knowledge absorption.

The multi-region numerical model is used to investigate the effect of foreign knowledge diffusion on domestic innovation and carbon savings in China. Simulation results show that foreign knowledge diffusion plays a crucial role to complement China's indigenous R&D to help stimulate technology innovation and reduce carbon emissions, contributing to about a quarter of domestic carbon savings resulting from endogenous TC. Foreign knowledge diffuses into China via three diffusion channels. In the short run, disembodied knowledge spillover is the leading diffusion channel, because there is a huge international disembodied knowledge pool (created by China's knowledge gap relative to technology frontier countries) accessible to China for learning and absorption. In the long run, China is anticipated to boost imports of knowledge-intensive high-tech products, and market-seeking MNCs seek to undertake more R&D-related FDI for new product development in the emerging markets. As an outcome, embodied knowledge diffusion through international trade and investment flows would become the leading pattern of international technology diffusion.

The results of globalization policy analysis also show that trade and FDI liberalization, as an indication of economic globalization policy, facilitates a transition to economic integration, which accelerates the growth momentum of production. However, without improving the intensity of knowledge embodied in import and FDI inflows, this expanding production size necessarily requires more uses of fossil energy without saving carbon emissions, reflecting the scale effect of globalization on the environment. Albeit this unfavorable effect, the multidimensional process of globalization also involves a favorable aspect: technique effect. That is, the growing globalization of innovation can be harnessed to acquire the benefit of domestic carbon saving, which depends on two conditions: 1) Removal of TD restrictions by technologically advanced nations to increase the intensity of knowledge embodied in foreign trade and investment; 2) Enhancement of indigenous R&D of the host developing countries to improve their capacities of knowledge absorption and adaptation.

Finally, it is indicated that a tightening of domestic climate regulation through carbon taxation can induce domestic firms to create new knowledge through indigenous R&D and foreign knowledge inflows. This innovation inducement thus plays an important role to help restructure domestic economic composition into a knowledge-based system (composition effect), which hence partially mitigate the economic cost of climate mitigation policies.

Chapter 5 employs both analytical and numerical methods to analyze the mechanism of international technology cooperation and its effect on global climate mitigation, with a focus on how multilateral R&D coordination (technology-oriented agreements) can synergize with traditional emission-based climate agreements to help lower the economic costs of emission control policies.

The central implication of the analytical results is that, in the absence of multilateral R&D coordination, individual countries undertake independent innovative activities but ignore the technology externality of cross-country knowledge diffusions. Accordingly, they underestimate the beneficial effect of indigenous R&D on fostering foreign innovation and emission reductions, and hence set R&D spending levels that are relatively low. In contrast, in the presence of multilateral R&D coordination, individual countries are instructed by a coordinating body to undertake higher levels of R&D spending for internalizing the positive technology externality. As a result, global collective innovative efforts would be enhanced, with more provisions of public knowledge that favors innovation and emissions reductions in participating countries.

The numerical simulation results are basically consistent with the analytical one. It is shown that: (1) By internalizing the positive externality of reciprocal knowledge diffusions, multilateral R&D coordination can induce more R&D efforts made by individual countries and hence the global provisions of knowledge that favor innovation across countries; (2) Innovative efforts enhanced by international R&D coordination facilitate new knowledge creation and application, which can stimulate the potential of economic growth and carbon savings in all participating countries (3) Multilateral R&D coordination (technology-oriented agreements) can synergize with traditional emission-based climate agreements to help lower the economic costs of emission control policies, hence improving the participation incentives of major carbon-emitting countries and the environmental effectiveness of their collective mitigation efforts in global climate governance.

6.2 Future work

So far my study in current work has articulated three key aspects associated with modelling endogenous TC in climate policy analysis, e.g., indigenous R&D investment (Chapter 3), international knowledge diffusion (Chapter 4), and international technology coordination (Chapter 5). Although the theoretical structure and modeling framework presented in this thesis is comprehensive, it is still needed to improve the empirical basis in future work.

First, while the collected benchmark dataset (e.g., multi-sector input-output transaction data, sector-level R&D data) provides a unique point for calibrating the theoretical model that features R&D-induced TC, it is common that there are more free parameters than there are model equations or observations of benchmark data. To pin down a solvable equilibrium, it is thus necessary to make assumptions about these free parameters (e.g., elasticity of substitutions, innovation possibility frontier parameters). This then raises the question of how precisely to determine the values of these exogenous parameters, which turn out to be a thorny issue. This difficulty is magnified in multi-sector, multi-region CGE modeling like in this study, where production technologies are specified using hierarchical CES functions, each of which has multiple elasticities of substitution. Basically, it is not possible to either estimate or compute theses elasticities without a host of auxiliary information. Faced with these data constraints, current works resort to selecting values for these parameters from the empirical literature based on judgment and assumptions. The ad-hoc nature of this process has been criticized by mainstream empirical economists who advocate an econometric approach to CGE modeling and parameterization (Jorgenson, 1984; McKitrick, 1998; McKibbin and Wilcoxen, 1999; Fisher-Vanden and Ho, 2007; van der Werf, 2008). Therefore, future efforts should be made to econometrically estimate the values of parameters.

Second, the other empirical weakness of the current model is about uncertainty. In a real-world economy with uncertainty, the possibility of substitution among production inputs may vary significantly among levels of the nested CES structure and across sectors. The parameters associated with the innovation possibility frontier (e.g., knowledge creation efficiency and elasticity) are also uncertain and heterogeneous across sectors. In this context, a model with deterministic parameter values thus ignores the inter-sectoral heterogeneity in substitution and innovation possibilities and the resulting uncertainty of policy simulation results. When faced with these sorts of issues, my current work typically undertakes a traditional sensitivity analysis to compare simulation results with different combinations of values for the various parameters in the model. However, given the arbitrarily chosen values for these parameters, this typical *ad-hoc* sensitivity analysis is far from sufficient to reflect the randomness (probability distribution) of these exogenous parameters. Hence, further efforts should be put on carrying out systematic sensitivity analysis using the techniques like Monte Carlo analysis and Gaussian Quadrature (e.g., Arndt, 1996; Liu, 1997; Pearson and Arndt, 2000; DeVuyst and Preckel, 1997; Webster and Cho, 2006). Applications of these structured uncertainty analysis (which employ empirically-derived probability distributions over input parameters) have the potential to enhance our understanding of the scope of uncertainties associated with the modeling results, and thereby help generate robust insights into the environmental, economic, and technological consequences in climate policy analysis.

Bibliography

Acemoglu, D., 2002. Directed technical change. Review of Economic Studies 69, 781-809.

Acemoglu, D., 2009. Introduction to Modern Economic Growth. Princeton University Press, Princeton, NJ, USA.

Acemoglu, D., Aghion, P., Bursztyn, L., Hemous, D., 2009. The environment and directed technical change. NBER Working Paper No. 15451. National Bureau of Economic Research.

Acharya, R., Keller, W., 2009. Technology transfer through imports. Canadian Journal of Economics 42, 1411-1448.

Aghion, P., Howitt, P., 1998. Endogenous Growth Theory. MIT Press, Cambridge, MA, USA.

Aitken, B., Harrison, A. 1999. Do domestic firms benefit from direct foreign investment? Evidence from Venezuela. American Economic Review 89, 605-618.

Aldy, J., Barrett, S., Stavins, R., 2003. Thirteen plus one: A comparison of global climate policy architectures. Climate Policy, 3(4), 373-397.

Amiti, M., Konings, J., 2007. Trade liberalization, intermediate inputs, and productivity: evidence from Indonesia. American Economic Review 97, 1611–1638.

Antweiler, W., Copeland, B., Taylor, S., 2000. Is free trade good for the environment? American Economic Review 91, 877-908.

Archibugi, D., Michie, J., 1997. Technology, Globalisation, and Economic Performance. Cambridge University Press, Cambridge, UK.

Archibugi, D., Iammarino, S., 1999. The policy implications of the globalisation of innovation. Research Policy 28, 317–36.

Archibugi, D., Michie, J., 1995. The globalisation of technology: A new taxonomy. Cambridge Journal of Economics 19, 121–40.

Armington, P., 1969. A theory of demand for products distinguished by place of production. IMF Staff Papers 16, 159-178.

Arndt, C., 1996. An introduction to systematic sensitivity analysis via Gaussian Quadrature. GTAP Technical Paper No. 2, 1996.

Arrow, K., 1969. Classificatory notes on the production and transmission of technological knowledge. American Economic Review Paper and Proceedings 59, 29-35.

Atkinson, A., Stiglitz, J., 1969. A new view of technological change. Economic Journal 79, 573-578.

Baker, E., Chon, H., Keisler, J., 2009. Advanced solar R&D: combining economic analysis with expert elicitations to inform climate policy. Energy Economics 31, S37-S49.

Baker, E., Clarke, L., Shittu, E., 2008. Technical change and the marginal cost of abatement. Energy Economics 30(6), 2799-2816.

Baker, E., Shittu, E., 2008. Uncertainty and endogenous technical change in climate policy models. Energy Economics 30 (6), 2817-2828.

Bibliography

Acemoglu, D., 2002. Directed technical change. Review of Economic Studies 69, 781-809.

Acemoglu, D., 2009. Introduction to Modern Economic Growth, Princeton University Press, Princeton, NJ, USA.

Acemoglu, D., Aghion, P., Bursztyn, L., Hemous, D., 2009. The environment and directed technical change. NBER Working Paper No. 15451. National Bureau of Economic Research.

Acharya, R., Keller, W., 2009. Technology transfer through imports. Canadian Journal of Economics 42, 1411-1448.

Aghion, P., Howitt, P., 1998. Endogenous Growth Theory. MIT Press, Cambridge, MA, USA.

Aitken, B., Harrison, A. 1999. Do domestic firms benefit from direct foreign investment? Evidence from Venezuela. American Economic Review 89, 605–618.

Aldy, J., Barrett, S., Stavins, R., 2003. Thirteen plus one: A comparison of global climate policy architectures. Climate Policy, 3(4), 373-397.

Amiti, M., Konings, J., 2007. Trade liberalization, intermediate inputs, and productivity: Evidence from Indonesia. American Economic Review 97, 1611–1638.

Antweiler, W., Copeland, B., Taylor, S., 2000. Is free trade good for the environment? American Economic Review 91, 877-908.

Archibugi, D. Michie, J., 1997. Technology, Globalization, and Economic Performance: Cambridge University Press, Cambridge, UK.

Archibugi, D., Iammarino, S., 1999. The policy implications of the globalization of innovation. Research Policy 28, 317–36.

Archibugi, D., Michie, J., 1995. The globalization of technology: A new taxonomy. Cambridge Journal of Economics 19, 121–40.

Armington, P., 1969. A theory of demand for products distinguished by place of production. IMF Staff Papers 16, 159-178.

Arndt, C., 1996. An introduction to systematic sensitivity analysis via Gaussian Quadrature. GTAP Technical Paper No. 2, 1996.

Arrow, K., 1969. Classificatory notes on the production and transmission of technological knowledge. American Economic Review Paper and Proceedings 59, 29–35.

Atkinson, A., Stiglitz, J., 1969. A new view of technological change. Economic Journal 79, 573-578.

Baker, E., Chon, H., Keisler, J., 2009. Advanced solar R&D: combining economic analysis with expert elicitations to inform climate policy. Energy Economics 31, S37-S49.

Baker, E., Clarke, L., Shittu, E., 2008. Technical change and the marginal cost of abatement. Energy Economics 30(6), 2799-2816.

Baker, E., Shittu, E., 2008. Uncertainty and endogenous technical change in climate policy models. Energy Economics 30 (6), 2817–2828.

Barrett, S., 2003. Environment and statecraft: The strategy of environmental treaty-making. Oxford University Press, Oxford, UK.

Barrett, S., 2006. Climate treaties and "breakthrough" technologies. American Economic Review, 96, 22-25.

Barrett, S., Stavins, R., 2003. Increasing participation and compliance in international climate change agreements", International Environmental Agreements: Politics, Law and Economics, 3 (4), 349 – 376.

Basu, S., Weil, D., 1998. Appropriate technology and growth. Quarterly Journal of Economics 113, 1025-1054.

Binswanger, H., 1974. A microeconomic approach to induced innovation. The Economic Journal 84, 940-958.

Blalock, G., Gertler, P., 2008. Welfare gains from foreign direct investment through technology transfer to local suppliers. Journal of International Economics 74, 402-421.

Blanford, G.J., 2009. R&D investment strategy for climate change. Energy Economics 31, S27-S36.

Blomström, M., Kokko, A., 1998. Multinational corporations and spillovers. Journal of Economic Surveys 12, 247–277.

Blomström, M., Kokko, A., 2003. The economics of foreign direct investment incentives. NBER Working Paper No. 9489. National Bureau of Economic Research.

Blomström, M., Persson, H., 1983. Foreign investment and spillover efficiency in an underdeveloped economy: Evidence from the Mexican manufacturing industry. World Development 11, 493–501.

Blonigen, B.A., 2005. A review of the empirical literature on FDI determinants. NBER Working Paper Series No 11299. National Bureau of Economic Research.

Böhringer, C., 1998. The synthesis of bottom-up and top-down in energy policy modeling. Energy Economics 20 (3), 234–248.

Bosetti, V., Carraro, C., Duval, R., Tavoni, M., 2011. What should we expect from innovation? A mode-based assessment of the environmental and mitigation cost implications of climate-related R&D. Energy Economics 33, 1313-1320.

Bosetti, V., Carraro, C., Massetti, E., Tavoni, M., 2008. International energy spillovers and the economics of green house gas atmospheric stabilization. Energy Economics 30, 2912-2929.

Bosetti, V., Massetti, E., Tavoni, M., 2007. The WITCH model: Structure, baseline, solution. FEEM Working Paper No 10-2007.

Bosetti, V., Tavoni, M., 2009. Uncertain R&D, backstop technology and GHG stabilization. Energy Economics 31, S18-S26.

Bovenberg, A.L., Goulder, L.H., 1996. Optimal environmental taxation in the presence of other taxes: general equilibrium analyses. American Economic Review 86, 985-1006.

Bresnahan, T., Trajtenberg, M., 1995. General purpose technologies: engines of growth? Journal of Econometrics 65. 83-108.

Brewer, T., 2008. Climate change technology transfer: A new paradigm and policy agenda.

Climate Policy 8, 516-526.

Brewer, T., 2009. Technology transfer and climate change: International flows, barriers and frameworks. In: Brainard L., Sorkin, I. (Eds.), Climate change, Trade and Competitiveness. The Brookings Institution, Washington, DC.

Brewer, T., Young, S., 1997. Investment incentives and the international agenda. World Economy 20, 175-198.

British Petroleum (BP), 2011. BP Energy Outlook 2030. London, U.K.

Brunnermeier, S., Levinson, A., 2004. Examining the evidence on environmental regulations and industry location. Journal of Economic Development 13, 6-41.

Buchner, B., Carraro, C., 2005. Economic and environmental effectiveness of a technology-based climate protocol. Climate Policy, 4, 229-248.

Buonanno, P., Carraro, C., Galeotti, M., 2003. Endogenous induced technical change and the costs of Kyoto. Resource and Energy Economics 25 (1), 11-34.

Bureau of Economic Analysis (BEA), 2007. Framework for an industry-based R&D satellite account. 2007 R&D Satellite Account Background Paper, Washington, DC.

Bye, B., Jacobsen, K., 2011. Restricted carbon emissions and directed R&D support: an applied general equilibrium analysis. Energy Economics 3, 543-555.

Carraro, C., 1998. Climate modelling and policy strategies: The role of technical change and uncertainty. Energy Economics 20, 463-471.

Carraro, C., Siniscaico, D., 1994. Environmental policy reconsidered: The role of technological innovation. European Economic Review 38, 545-554

Carraro, C., Siniscalco, D., 1997. R&D cooperation and the stability of international environmental agreements. In: Carraro C. (Ed), International Environmental Negotiations: Strategic Policy Issues. Edward Elgar Publishing.

Clarke, L., Weyant, J., Birky, A., 2006. On the sources of technological advance: assessing the evidence. Energy Economics 28 (5), 579–595.

Clarke, L., Weyant, J., Edmonds, J., 2008. On the sources of technological advance: what do the models assume? Energy Economics 30 (2), 409–424.

Clerides, S., Lach, S., Tybout, J., 1998. Is learning by exporting important? Micro-dynamic evidence from Colombia, Mexico, and Morocco. Quarterly Journal of Economics 113, 903–948.

Codsi, G., Pearson, K., Wilcoxen, P., 1992. General-purpose software for intertemporal economic models. Computer Science in Economics and Management 5, 57-79.

Coe, D., Helpman, E., 1995. International R&D spillovers. European Economic Review 39 (5), 859–887.

Coe, D., Helpman, E., Hoffmaister, A., 1997. North-South R&D spillovers. Economic Journal 107, 134–49.

Cohen, W., Levinthal, D., 1989. Innovation and learning: the two faces of R&D. The Economic Journal 99, 569–596.

Cole, M., Elliott, R., 2003. Determining the trade-environment composition effect: The role of capital, labor and environmental regulations. Journal of Environmental Economics and Management 46, 363-383.

Copeland, B., Taylor, S., 2003. Trade and the Environment: Theory and Evidence. Princeton University Press, Princeton NJ, USA.

Copeland, B., Taylor, S., 2004. Trade, growth, and the environment. Journal of Economic Literature 42, 7-71.

David, P., Hall, B., 2000. Heart of darkness: modeling public-private funding interactions inside the R&D black box, Research Policy, 29(9), 1165-1183.

David, P., Hall, B., Toole, A., 2000. Is public R&D a complement or substitute for private R&D? A review of the econometric evidence, Research Policy, v29(4-5), 497-529.

De Cian, E., Tavoni, M., 2012. Do technology externalities justify restrictions on emission permit trading ? Resource and Energy Economics, 34, 624-646.

De Coninck, H., Fischer, C., Newell, R., Ueno, T., 2008. International technology-oriented agreements to address climate change. Energy Policy 36:335-356.

De la Toura, A., Glachanta, M., Ménière, Y., 2011. Innovation and international technology transfer: the case of the Chinese photovoltaic industry. Energy Policy 39, 761-770.

Dechezleprêtre, A., Glachant, M., Meniere, Y., 2008. The Clean Development Mechanism and the international diffusion of technologies: An empirical study. Energy Policy 36:1273-1283.

DeVuyst, E., Preckel, P., 1997. Sensitivity analysis revisited: A Quadrature-based approach. Journal of Policy Modeling, 19(2):175-185.

Dixon, P., Pearson, K., Picton, M., Rimmer, M., 2005. Rational expectations for large CGE models: a practical algorithm and a policy application. Economic Modelling 2, 1001–1019.

Eaton, J., Kortum, S., 1999. International patenting and technology diffusion: theory and measurement. International Economic Review 40, 537–570.

Eaton, J., Kortum, S., 2001. Trade in capital goods. European Economic Review 45, 1195–1235.

Eaton, J., Kortum, S., 2002. Technology, geography, and trade. Econometrica 70, 1741–1780.

EMF (Energy Modeling Forum), 2004. EMF 19 Alternative technology strategies for climate change policy. J. P. Weyant (Ed.), Special Issue of Energy Economics 26: 501-755.

Energy Information Administration (EIA), 2010. International Energy Outlook 2010. U.S. Department of Energy, Washington DC.

Fisher-Vanden, K., Ho, M., 2007. How do market reforms affect China's responsiveness to environmental policy? Journal of Development Economics 82(1), 200-233.

Flavin, M., 1981. The adjustment of consumption to changing expectations about income. Journal of Political Economy 89, 974–1009.

Frankel, J., 2003. The environment and globalization. NBER Working Paper No. 10090. National Bureau of Economic Research.

Freeman, R. 2006. Does globalization of the scientific and engineering workforce threaten US economic leadership? In: Jaffe, A.B., Lerner, J., Stern, S. (Eds.), Innovation policy and the economy. MIT Press, Cambridge, MA, USA.

Freeman, R., 2010. Globalization of scientific and engineering talent: international mobility of students, workers, and ideas and the world economy. Economics of Innovation and New Technology 19, 393-406.

Freitas, I.M.B., Dantas, E., Iizuka, M., 2012. The Kyoto mechanisms and the diffusion of renewable energy technologies in the BRICS. Energy Policy 42, 118-128.

Gerlagh, R., Kuik, O., 2007. Carbon leakage with international technology spillovers. FEEM Working Paper No. 33.2007.

Gerlagh, R., van der Zwann, B., 2003. Gross world product and consumption in a global warming model with endogenous technological change. Resource and Energy Economics 25 (1), 35–37.

Gerschenkron, A., 1962. Economic Backwardness in Historical Perspective. Harvard University Press, Cambridge, MA, USA.

Gillingham, K., Newell, R., Pizer, W., 2008. Modeling endogenous technological change for climate policy analysis. Energy Economics 30, 2734-2753.

Golombek, R., Hoel, M., 2005. Climate policy under technology spillovers. Environmental and Resource Economics, 31, 201-227.

Golombek, R., Hoel, M., 2008. Endogenous technology and tradable emission quotas. Resource and Energy Economics, 30, 197-208.

Golombek, R., Hoel, M., 2011. International cooperation on climate-friendly technologies. Environmental and Resource Economics, 49, 473-490.

Goolsbee, A., 1998. Does government R&D policy mainly benefit scientists and engineers? American Economic Review 88, 298–302.

Goulder, L., Mathai, K., 2000. Optimal CO_2 abatement in the presence of induced technological change. Journal of Environmental Economics and Management 39, 1–38.

Goulder, L., Schneider, S., 1999. Induced technological change and the attractiveness of CO_2 abatement policies. Resource and Energy Economics 21, 211-253.

Greaker M., Hagem, C., 2010. Strategic investment in climate friendly technologies: the impact of permit trade. Discussion Papers, Research Department of Statistics Norway

Griffith, R., Redding, S., Van Reenen, J., 2004. Mapping two faces of R&D: Productivity growth in a panel of OECD industries. Review of Economics and Statistics 86, 883-895.

Griliches, Z., 1979. Issues in assessing the contribution of R&D to productivity growth. Bell Journal of Economics 10, 92–116.

Griliches, Z., 1992. The search for R&D spillovers. Scandinavian Journal of Economics 94, S29-S47.

Griliches, Z., Lichtenberg, F., 1984. Interindustry technology flows and productivity growth: a re-examination. The Review of Economics and Statistics 66, 324-29.

Grossman, G., Helpman, E., 1994. Endogenous innovation in the theory of growth. Journal of Economic Perspectives 8, 23-44.

Grubb, M., 1997. Technologies, energy systems, and the timing of CO_2 abatement: An Overview of Economic Issues. Energy Policy 25, 159-172.

Grubb, M., Hope, C., Fouquet, R., 2002. Climatic implications of the Kyoto Protocol: The contribution of international spillover. Climatic Change 54, 11–28.

Grübler, A., Messner, S., 1998. Technological change and the timing of mitigation measures. Energy Economics 20, 495–512.

Grübler, A., Nakicenovic, N., Victor, D., 1999. Modeling technological change: Implications for the global environment. Annual Review of Energy and the Environment, 24, 545-569.

Gupta, S., D. A. Tirpak, N. Burger, J. Gupta, N. Höne, A. I. Boncheva, G. M. Kanoan, C. Kolstad, J. A. Kruger, A. Michaelowa, S. Murase, J. Pershing, T. Saijo, A. Sari, 2007: Policies, Instruments and Co-operative Arrangements. In Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [B. Metz, O.R. Davidson, P.R. Bosch, R. Dave, L.A. Meyer (eds)], Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Haddad, M., Harrison, A., 1993. Are there positive spillovers from direct foreign investment? Evidence from panel data for Morocco. Journal of Development Economics 42, 51-74.

Hall, B., 2002. The assessment: technology policy, Oxford Review of Economic Policy, Oxford University Press, 18(1), 1-9

Hall, B., 2002. The financing of research and development, Oxford Review of Economic Policy, Oxford University Press, 18(1), 35-51.

Hall, B., Van Reenen, J., 2000. How effective are fiscal incentives for R&D? A review of the evidence, Research Policy, 29(4-5), 449-469.

Hall, R., 1978. Stochastic implications of the life cycle-permanent income hypothesis: theory and evidence. Journal of Political Economy 86, 971–87.

Harrison, W., Pearson, K., 1996. Computing solutions for large general equilibrium models using GEMPACK. Computational Economics 9, 83-127.

Haskel, J., Pereira, S., Slaughter, M. 2007. Does inward foreign direct investment boost the productivity of domestic firms? Review of Economics and Statistics 89, 482–496.

Hauknes, J., Knell, M., 2009. Embodied knowledge and sectoral linkages: An input–output approach to the interaction of high- and low-tech industries. Research Policy 38, 459-469.

Hayashi, F., 1982. Tobin's marginal q and average q: a neoclassical interpretation. Econometrica 50, 213–224.

Hayek, F., 1945. The use of knowledge in society. American Economic Review 35, 519–530.

Heal, G., Tarui, N., 2010. Investment and emission control under technology and pollution externalities. Resource and Energy Economics, 32, 1-14.

Held, H., Kriegler, E., Lessmann, K., Edenhofer, E., 2009. Efficient climate policies under technology and climate uncertainty. Energy Economics S50-S61.

Helm C., Pichler, S., 2011. Climate policy with technology transfer and permit trading. Working papers, University of Oldenburg. Department of Economics.

Helm, C., Wirl, F., 2011. International environmental agreements: Incentive contracts with multilateral externalities. Working papers, University of Oldenburg. Department of Economics.

Helpman, E., 1998. General purpose technologies and economic growth. MIT Press.

Heutel, G., Fischer, C., 2013. Environmental macroeconomics: Environmental policy, business cycle, and directed technical change. NBER Woking Paper No. 18794

Hicks, J., 1932. The theory of wages. Macmillan, London, UK.

Hoel, M., de Zeeuw, A., 2010. Can a focus on breakthrough technologies improve the performance of international environmental agreements? Environmental and Resource Economics, 47, 395-406.

Hübler, M., 2011. Technology diffusion under contraction and convergence: A CGE analysis of China, Energy Economics 33, 131-142.

Intergovernmental Panel on Climate Change (IPCC), 2000. In: Nakicenovic, N., Swart, R. (Eds.), Special report on emissions scenarios. Cambridge University Press, Cambridge.

Intergovernmental Panel on Climate Change (IPCC), 2000. Methodological and technological issues in technology transfer. Cambridge University Press, Cambridge, UK.

International Energy Agency (IEA), 2007. World Energy Outlook – China and India Insights. OECD, Paris.

International Energy Agency (IEA), 2010. World Energy Outlook 2010. OECD, Paris.

International Monetary Fund (IMF), 2011. Changing Patterns of Global Trade. IMF, Washington, D.C.

Jacoby, H., Reilly, J., McFarland, J., Paltsev, S., 2004. Technology and technical change in the MIT EPPA model. Joint Program on the Science and Policy of Global Change Report no. 111. Massachusetts Institute of Technology, Cambridge, MA.

Jaffe, A., Newell, R., Stavins, R., 2003. Technological change and the environment. In: Maler, K.-G., Vincent, J.R. (Eds.), Handbook of Environmental Economics, vol. 1. Elsevier, Washington, DC.

Jaffe, A., Trajtenberg, M., 1998. International knowledge flows: Evidence from patent citations. NBER Working Paper No. 6507. National Bureau of Economic Research.

Jaffe, A.B., Newell, R.G., Stavins, R.N., 2005. A tale of two market failures: technology and environmental policy. Ecological Economics 54, 164–174.

Jakeman, G., Hanslow, K., Hinchy, M., Fisher, B., Woffenden, K., 2004. Induced innovations and climate change policy. Energy Economics 26 (6), 937–960.

Javorcik, B. S., 2004. Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages. American Economic Review 94, 605–627.

Jin, W., 2012. Can technological innovation help China take on its climate responsibility? An intertemporal general equilibrium analysis. Energy Policy 49, 629-641.

Johnstone, N., Hascic, I., Popp, D., 2010. Renewable energy policies and technological innovation: evidence based on patent counts. Environmental and Resource Economics 45, 133-155.

Jorgenson, D., 1984. Econometric methods for applied general equilibrium analysis. In H. Scarf and J. B. Shoven (Eds.), Applied General Equilibrium Analysis, pp. 139-207. Cambridge: Cambridge University Press.

Jorgenson, D., Wilcoxen, P., 1990. Intertemporal general equilibrium modeling of U.S. environmental regulation. Journal of Policy Modeling 12, 715- 744.

Kahrl, F., Williams, J., Ding, J., Hu, J., 2011. Challenges to China's transition to a low carbon electricity system. Energy Policy 39, 4032–4041.

Kamien, M., Schwartz, N., 1968. Optimal induced technical change. Econometrica 36, 1–17.

Kaya, Y., 1990. Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios. IPCC Response Strategies Working Group, Paris.

Keller, W., 1996. Absorptive capacity: on the creation and acquisition of technology in development. Journal of Development Economics 49, 199-227.

Keller, W., 1998. Are international R&D spillovers trade related? Analyzing spillovers among randomly matched trade partners. European Economic Review 42, 1469–81.

Keller, W., 2001. Knowledge spillovers at the world's technology frontier. CEPR Working Paper No. 2815.

Keller, W., 2002. Geographic localization of international technology diffusion. American Economic Review 92, 120–142.

Keller, W., 2004. International Technology Diffusion. Journal of Economic Literature 42, 752–782.

Keller, W., Yeaple, S. 2009. Multinational enterprises, international trade, and productivity growth: firm-level evidence from the United States. Review of Economics and Statistics 91, 821-831.

Kemfert, C., 2004. Climate coalitions and international trade: assessment of cooperation incentives by issue linkage. Energy Policy 32, 455–465.

Kennedy, C., 1964. Induced bias in innovation and the theory of distribution. The Economic Journal 74, 541–547.

Kolstad, C., 2007 Systematic uncertainty in self-enforcing international environmental agreements. Journal of Environmental Economics and Management 53(1): 68–79

Kraay, A., Soloaga, I., Tybout, J., 2002. Product quality, productive efficiency, and international technology diffusion: evidence from plant-level panel data. World Bank Policy Research Working Paper No. 2759.

Kuik, O., Gerlagh, R., 2003. The effect of trade liberalization on carbon leakage under the Kyoto Protocol. The Energy Journal 24, 97-120.

Kypreos, S., Turton, H., 2011. Climate change scenarios and technology transfer protocols, Energy Policy 39, 844-853.

Lanjouw, J., Mody, A., 1996. Innovation and the international diffusion of environmentally responsive technology. Research Policy 25, 549–571.

Lee, G., 2006. The effectiveness of international knowledge spillover channels. European Economics Review 50, 2075-2088

Leimbach, M., Baumstark, L., 2010. The impact of capital trade and technological spillovers on climate policies. Ecological Economics 69, 2341–2355.

Leimbach, M., Edenhofer, O., 2007. Technological spillovers within multi-region models: intertemporal optimization beyond the Negishi approach. Economic Modelling 24, 272–294.

Leimbach, M., Eisenack, K., 2009. A trade algorithm for multi-region models subject to spillover externalities. Computational Economics 33, 107–130.

Lejour, A., Rojas-Romagosa, H., Verweij, G., 2008. Opening services markets within Europe: Modelling foreign establishments in a CGE framework. Economic Modelling 25, 1022-1039.

Lessman, Kai and Ottmar Edenhofer (2011). "Research Cooperation and International Standards in a Model of Coalition Stability." Resource and Energy Economics, 33, 36-54.

Lin, P., Saggi, K., 2007. Multinationals, exclusivity, and the degree of backward linkages. Journal of International Economics 71, 206–220.

Liu, S., 1997. Gaussian Quadrature and its applications. PhD Dissertation, Department of Agricultural Economics, Purdue University, 1997.

Löschel, A., 2002. Technological change in economic models of environmental policy: a survey. Ecological Economics 43, 105-126.

Löschel, A., Otto, V., 2009. Technological uncertainty and cost effectiveness of CO2 emission reduction. Energy Economics 31, S4-S17

Lovely, M., Popp, D., 2011. Trade, technology and the environment: Does access to technology promote environmental regulation? Journal of Environmental Economics and Management 61, 16–35.

Lucas, R., 1967. Adjustment costs and the theory of supply. Journal of Political Economy 75, 321-334.

MacCracken, C., Edmonds, J., Kim, S., Sands, R., 1999. The economics of the Kyoto protocol. The Energy Journal 25–72 Special Issue.

Madsen, J., 2007. Technology spillovers through trade and TFP convergence: 135 years of evidence for OECD countries. Journal of International Economics 72, 464–480.

Mai, Y., 2005. The MONASH-Multi-Country model and the investment liberalization in China's oil industry. Centre of Policy Studies Working Paper G-150, Monash University.

Malakellis, M., 1994. ORANI-IN: an intertemporal computable general equilibrium model of the Australian Economy. Ph.D Thesis, Monash University.

Manne, A., Barreto, L., 2004. Learning-by-doing and carbon dioxide abatement. Energy Economics 26, 621–633

Manne, A., Richels, R., 2004. The impact of learning-by-doing on the timing and costs of CO2 abatement. Energy Economics 26, 603–619.

Mansfield, E., 1996. Contribution of new technology to the economy. In: Smith, B.L.R., Barfield, C.E. (Eds.), Technology, R&D, and the Economy. Brookings Institution and American Enterprise Institute, Washington.

Maria, C., Werf, E., 2008. Carbon linkage revisited: unilateral climate policy with directed technical change. Environmental & Resource Economics. 39: 55-74

Markusen, J., 2002. Multinational Firms and the Theory of International Trade. MIT Press.

McFarland, J.R., Reilly, J.M., Herzog, H.J., 2004. Representing energy technologies in top-down economic models using bottom-up information. Energy Economics 26, 685–707.

McKibbin W., Wilcoxen, P., 1999. The theoretical and empirical structure of the G-Cubed model. Economic Modelling 16, 123-148.

McKibbin, W., 2008. China and the global environment. In B. Eichengreen, Y.C. Park, C. Wyplosz (Eds.), China, Asia and the new world economy, Oxford University Press, pp. 18-50

McKibbin, W., Morris A., Wilcoxen P., 2011. Comparing climate commitments: A model-based analysis of the Copenhagen Accord, Climate Change Economics 2, 79-103.

McKibbin, W., Wilcoxen, P., 2004. Estimates of the costs of Kyoto-Marrakesh versus the McKibbin-Wilcoxen blueprint. Energy Policy 32, 467-479.

McKibbin, W., Wilcoxen, P., 2009. Uncertainty and climate change policy design. Journal of Policy Modeling 31, 463-477.

McKitrick, R., 1998. The econometric critique of applied general equilibrium modelling: The role of functional forms. Economic Modelling 15, 543-573.

Ministry of Science and Technology (MOST), 2006a. China Statistical Yearbook on Science and Technology 2006. National Bureau of Statistics, China Statistics Press, Beijing.

Ministry of Science and Technology (MOST), 2006b. National Guidelines for Medium- and Long-term Plans for Science and Technology Development of China, 2006-2020. Beijing.

Modigliani, F., 1976. Life-cycle, individual thrift, and the wealth of nations. American Economic Review 76, 297–313.

Mowery, D., Rosenberg, N., 1979. Influence of market demand upon innovation — critical-review of some recent empirical-studies. Research Policy 8, 102–153.

Nagashima, M., Dellink, R., 2008. Technology spillovers and stability of international climate coalitions. International Environmental Agreements: Politics, Law and Economics 8 (4), 343–365.

Narayanan, B., Walmsley, T., 2008. Global Trade, Assistance, and Production: The GTAP 7 Data Base. Center for Global Trade Analysis, Purdue University.

National Bureau of Statistics (NBS), 2011. China Statistical Yearbook 2010. China Statistics Press, Beijing.

National Science Board (NSB). 2012. Science and Engineering Indicators. Arlington, VA: National Science Foundation.

Nelson, R., 1993. National innovation systems: A comparative analysis, Oxford University Press, New York and Oxford.

Nelson, R., Phelps, E., 1966. Investment in humans, technological diffusion and economic growth. American Economic Reviews 56, 69-75.

Newell, R., International climate technology strategies. Discussion Paper 2008-12, Cambridge, Mass.: Harvard Project on International Climate Agreements, October 2008

Newell, R., Jaffe, A., Stavins, R., 1999. The induced innovation hypothesis and energy-saving technological change. Quarterly Journal of Economics 114, 941–975.

Nordhaus, W., 1969. Invention, growth and welfare: a theoretical treatment of technological change. M.I.T Press. Cambridge, MA.

Nordhaus, W., 1994. Managing the Global Commons: The Economics of Climate Change. MIT Press, Cambridge, MA.

Nordhaus, W., 2002. Modeling induced innovation in climate change policy. In: Grubler, A., Nakicenovic, N., Nordhaus, W. (Eds.), Technological Change and the Environment. Resources for the Future Press, Washington, DC.

Nordhaus, W., 2011. Designing a friendly space for technological change to slow global warming. Energy Economics 33, 665-673.

OECD, 1997. Internationalization of Industrial R&D: Patterns and Trends. Groups of National Experts on Science and Technology Indicators, OECD, Paris.

OECD, 2008. Reviews of Innovation Policy: China 2008. OECD, Paris.

OECD, 2010. OECD Science, Technology and Industry Outlook. OECD, Paris.

OECD, 2012. Main Science and Technology Indicators. Paris: OECD.

Otto, V., Löschel, A., Dellink, R., 2007. Energy biased technical change: a CGE analysis. Resource and Energy Economics 29, 137–158.

Otto, V., Löschel, A., Reilly, J., 2008. Directed technical change and differentiation of climate policy. Energy Economics 30 (6). 2855-2878

Otto, V., Reilly, J., 2008. Directed technical change and the adoption of CO2 abatement technology: the case of CO2 capture and storage. Energy Economics 30, 2879-2898.

Papaconstantinou, G., Sakurai, N., Wyckoff, A., 1998. Domestic and international product-embodied R&D diffusion. Research Policy 27, 301–314.

Pavcnik, N., 2002. Trade liberalization, exit, and productivity improvements: Evidence from Chilean plants. Review of Economic Studies 69, 245–276.

Pearson, K., Arndt, C., 2000. Implementing systematic sensitivity analysis using GEMPACK. GTAP Technical Paper No. 3, 1996, revised 2000.

Petri, P., 1997. Foreign direct investment in a CGE framework. Paper Prepared for the Conference on Making APEC work: Economic Challenges and Policy Alternatives, March 13-14. Keio University, Tokyo.

Philibert, C., 2004. International Energy Technology Collaboration and Climate Change Mitigation. OECD Environment Directorate and International Energy Agency, Paris.

Pizer, W., Popp, D., 2008. Endogenizing technological change: matching empirical evidence to modeling needs. Energy Economics 30, 2754-2770.

Polanyi, M., 1958. Personal knowledge: Towards a post-critical philosophy. University of Chicago Press, Chicago, IL.

Popp, D., 2002. Induced innovation and energy prices. American Economic Review 92, 160–180.

Popp, D., 2004. ENTICE: endogenous technological change in the DICE model of global warming. Journal of Environmental Economics and Management 48, 742–768.

Popp, D., 2005. Lessons from patents: Using patents to measure technological change in environmental models. Ecological Economics 54, 209-226.

Popp, D., 2006a. Innovation in climate policy models: Implementing lessons from the economics of R&D. Energy Economics 28, 596-609.

Popp, D., 2006b. International innovation and diffusion of air pollution control technologies: The effects of NO_X and SO_2 regulation in the U.S., Japan, and Germany. Journal of Environmental Economics and Management 51: 46–71.

Popp, D., 2009. International technology transfers for climate change: A perspective on the proposal by Zili Yang. Prepared for the Copenhagen Consensus on Climate.

Popp, D., 2011. International technology transfer, climate change, and the clean development mechanism. Review of Environmental Economics and Policy 5, 131-152.

Popp, D., Hascic, I., Medhi, N., 2010a. Technology and the diffusion of renewable energy. Energy Economics 33, 648-662.

Popp, D., Newell, R., Jaffe, A., 2010b. Energy, the environment, and technological change. In: Hall, B., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation. Academic Press.

Porter, M., van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. Journal of Economic Perspectives 9, 97-118.

Rivera-Batiz, L., Romer, P., 1991. Economic integration and endogenous growth. Quarterly Journal of Economics 106, 531–555.

Rodriguez-Clare, A., 1996. Multinationals, linkages, and economic development. American Economic Review 86, 852–873.

Romer, P., 1990. Endogenous technological change. Journal of Political Economy 98, S71-S102.

Rosenberg, N., 1994. Exploring the Black Box: Technology, Economics, and History. Cambridge University Press. Cambridge, United Kingdom.

Scherer, F., 1982. Interindustry technology flows in the US. Research Policy 11, 227-245.

Schmookler, J., 1966. Invention and Economic Growth. Harvard University Press, Cambridge, MA.

Shi, Y., Rao, Y., 2010. China's research culture. Science 329, 1128.

Springer, K., 1998. The DART general equilibrium model: A technical description. Kiel Working Paper 883.

Stavins, R., 2011. The problem of the commons: still unsettled after 100 Years. American Economic Review 101, 81-108.

Stern, N., 2007. The economics of climate change: the Stern review. Cambridge University Press, Cambridge, UK.

Stiglitz, J., 2006. Making Globalization Work. W.W. Norton & Company. New York.

Sue Wing, I., 2001. Induced technical change in computable general equilibrium models for climate policy analysis. Ph.D. Dissertation, MIT, Cambridge, MA.

Sue Wing, I., 2003. Induced technical change and the cost of climate policy. Joint Program on the Science and Policy of Global Change Report no. 112. MIT, Cambridge, MA.

Sue Wing, I., 2006. Representing induced technological change in models for climate policy analysis. Energy Economics 28, 539-562.

Summers, L., 1981. Taxation and corporate investment: A q-theory approach. Brookings Papers on Economic Activity no. 1, 67-127.

System of National Accounts (SNA), 2008. Commission of the European Communities, International Monetary Fund, Organization for Economic Co-operation and Development, and World Bank.

Taylor, M., 2008. Beyond technology-push and demand-pull: lessons from California's solar policy. Energy Economics 30, 2829-2854.

Terleckyj, N., 1974, Effects of R&D on the productivity growth of industries: An exploratory study. National Planning Association, Washington DC.

Tobin, J., 1969. A general equilibrium approach to monetary theory. Journal of Money, Credit and Banking 1, 15-29.

Treadway, A., 1969. On rational entrepreneurial behavior and the demand for investment. Review of Economic Studies 36, 227-240.

UNCTAD, 2005. World Investment Report 2005: TNCs and the Internationalization of R&D. United Nations publications, New York and Geneva.

UNCTAD, 2010a. Trade and Development Report 2011: Employment, Globalization and Development. United Nations publications, New York and Geneva.

UNCTAD, 2010b. World Investment Report 2011: Investing in a Low-carbon Economy. United Nations publications, New York and Geneva.

UNFCCC, 2007a. Investment and Financial Flows to Address Climate Change. UNFCCC, Bonn.

UNFCCC, 2007b. Work Programme of the Expert Group on Technology Transfer (EGTT) for 2007. UNFCCC, Bonn.

van der Werf, E., 2008. Production functions for climate policy modeling: an empirical analysis. Energy Economics 30, 2964-2979.

van Meijl, H., van Tongeren, F., 1999. Endogenous international technology spillovers and biased technical change in the GTAP model. GTAP Technical Paper No. 15.

Verdolini, E., Galeotti, M. 2011. At home and abroad: An empirical analysis of innovation and diffusion in energy technologies. Journal of Environmental Economics and Management 61, 119-134.

Wang, K., Wang, C., Chen, J. 2009. Analysis of the economic impact of different Chinese climate policy options based on a CGE model incorporating endogenous technological change. Energy Policy 37, 2930-2940.

Webster, M., Cho, C., 2006. Analysis of variability and correlation in long-term economic growth rates. Energy Economics 28, 653-666.

Wendner, R., 1999. A calibration procedure of dynamic CGE models for non-steady state situations using GEMPACK. Computational Economics 13, 265-287.

Wolf, M., 2005. Why Globalization Works. Yale University Press. New Haven and London.

World Bank, 2007. An Investment Framework for Clean Energy and Development. Washington, DC: World Bank.

World Bank, 2011. World Development Indicators 2011. World Bank, Washington, DC.

World Bank. 2008. Global Economic Prospects: Technology Diffusion in the Developing World. Washington, DC: World Bank.

World Trade Organization (WTO), 2010. World Trade Report 2011. WTO, Geneva.

Xepapadeas, A., 1995. Induced technical change and international agreements under greenhouse warming. Resource and Energy Economics, 17, 1-23.

Xu, B., 2000. Multinational enterprises, technology diffusion, and host country productivity growth. Journal of Development Economics 62, 477–493.

Xu, B., Wang, J., 1999. Capital goods trade and R&D spillovers in the OECD. Canadian Journal of Economics 32, 1258–1274.

Yang, Z., Nordhaus, W., 2006. Magnitude and direction of technological transfers for mitigating GHG emissions. Energy Economics 28, 730-741.

Zhang, Z.X., 2011. Assessing China's carbon intensity pledge for 2020: stringency and credibility issues and their implications. Environmental Economics and Policy Studies 13, 219-235.